PA model development, optimization and evaluation

Random Forest regressor and classifier

This is a project to use all steps needed to develop a best fit PA model, it include 3 main steps:

1. data selection and EDA
2. Data Preparation
3. Model building and evaluation

1. Data selection and EDA

I am interested to know which factor may impact income most and how much the impacts are. This is also a topic impact anyone who has a job and want to make a decent living by earning income.

After few rounds of search, I picked a dataset from kaggle, which is with income information and suitable for data mining/machine learning.

This dataset originates from the 1994 Census Bureau database with information of adult (human being aged >16) income. The income is categorized into 2 gourps (>50K or <50K). it also contains 11 independent variables like age, workclass, education and martial status etc. The only variable need to explain is fnlwgt: Final weight. This is an estimation of the number of people each observation in the dataset represents in the population.

The first step is to select and load data, then preform EDA to visualized the data and understand basic relationship/correlation of the variables.

Data checking and cleaning

In [1]:
```
# Load packages first
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#load the data and validate success
```

```
df = pd.read_csv('adult income.csv')
df.head(5)
```

Out[1]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex	native.country	income
0	17	Private	148522	11th	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
1	17	Private	93235	12th	8	Never-married	occupation	Own-child	White	Female	United-States	<=50K
2	17	Private	184924	9th	5	Never-married	occupation	Own-child	White	Male	United-States	<=50K
3	17	Private	116626	11th	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
4	17	Private	209949	11th	7	Never-married	occupation	Own-child	White	Female	United-States	<=50K

In [2]:

```
#check the data info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31947 entries, 0 to 31946
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             31947 non-null  int64 
 1   workclass       31947 non-null  object
 2   fnlwgt          31947 non-null  int64 
 3   education       31947 non-null  object
 4   education.num   31947 non-null  int64 
 5   marital.status  31947 non-null  object
 6   occupation      31947 non-null  object
 7   relationship    31947 non-null  object
 8   race            31947 non-null  object
 9   sex             31947 non-null  object
 10  native.country  31947 non-null  object
 11  income          31947 non-null  object
dtypes: int64(3), object(9)
memory usage: 2.9+ MB
```

In [2]:

```
# exam column and NA
print('variables with NA values', df.isna().sum())
```

```
variables with NA values age              0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
native.country    0
income            0
dtype: int64
```

In [3]:
```
# check if income is balanced.
count=len(df[df['income']=="<=50K"])
count1=len(df[df['income']==">50K"])
print('high/low income sample ratio is:', round(count1/count,2))
```

```
high/low income sample ratio is: 0.32
```

In [5]:
```
# the income sample is not balanced.
```

In [4]:
```
# Rename column name with dot
df.rename(columns = {'education.num':'education_len'}, inplace = True)
df.rename(columns = {'marital.status':'marital_status'}, inplace = True)
df.tail()
```

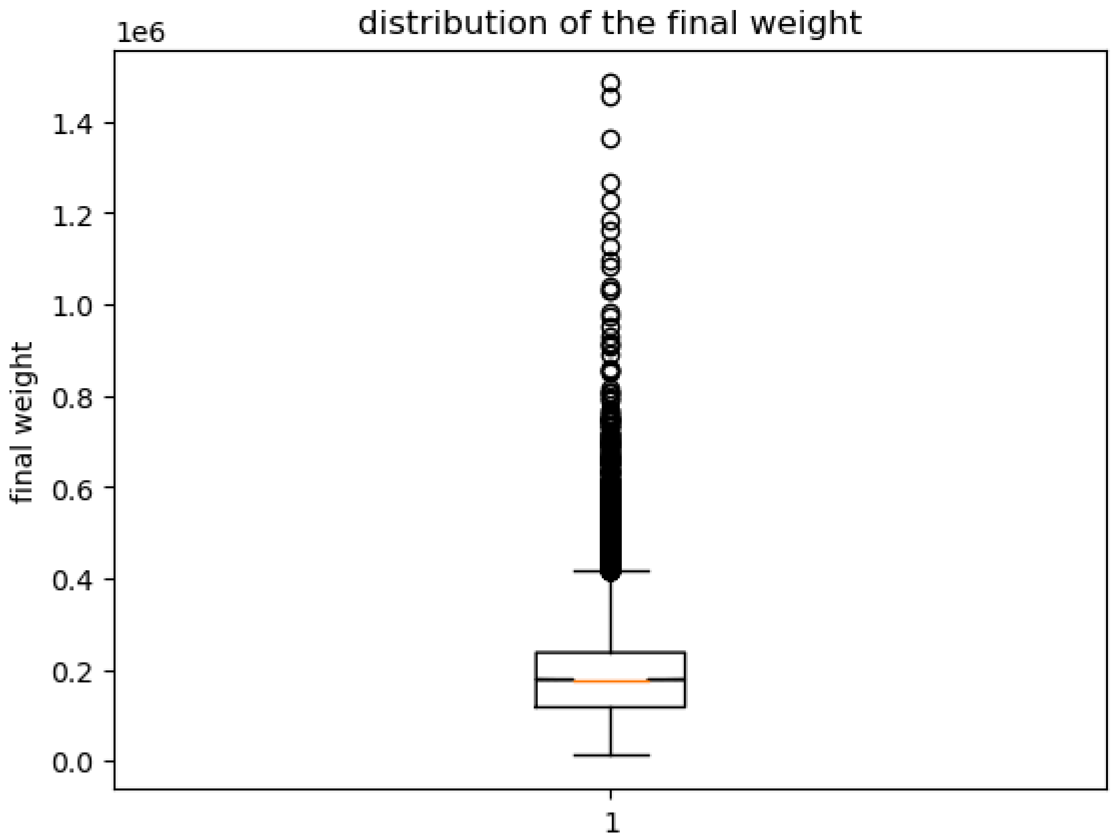
Out[4]:

	age	workclass	fnlwgt	education	education_len	marital_status	occupation	relationship	race	sex	native.country	income
31942	90	?	175444	7th-8th	4	Separated	?	Not-in-family	White	Female	United-States	<=50K
31943	90	Federal-gov	195433	HS-grad	9	Married-civ-spouse	Craft-repair	Husband	White	Male	United-States	<=50K
31944	90	Private	47929	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	United-States	<=50K
31945	90	?	313986	HS-grad	9	Married-civ-spouse	?	Husband	White	Male	United-States	>50K
31946	90	Private	313749	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	United-States	<=50K

start the visualization

In [5]:
```
# box chart of fnlwight (final weight)
plt.boxplot(df.fnlwgt, notch=True)
plt.title('distribution of the final weight')
plt.ylabel('final weight')
```

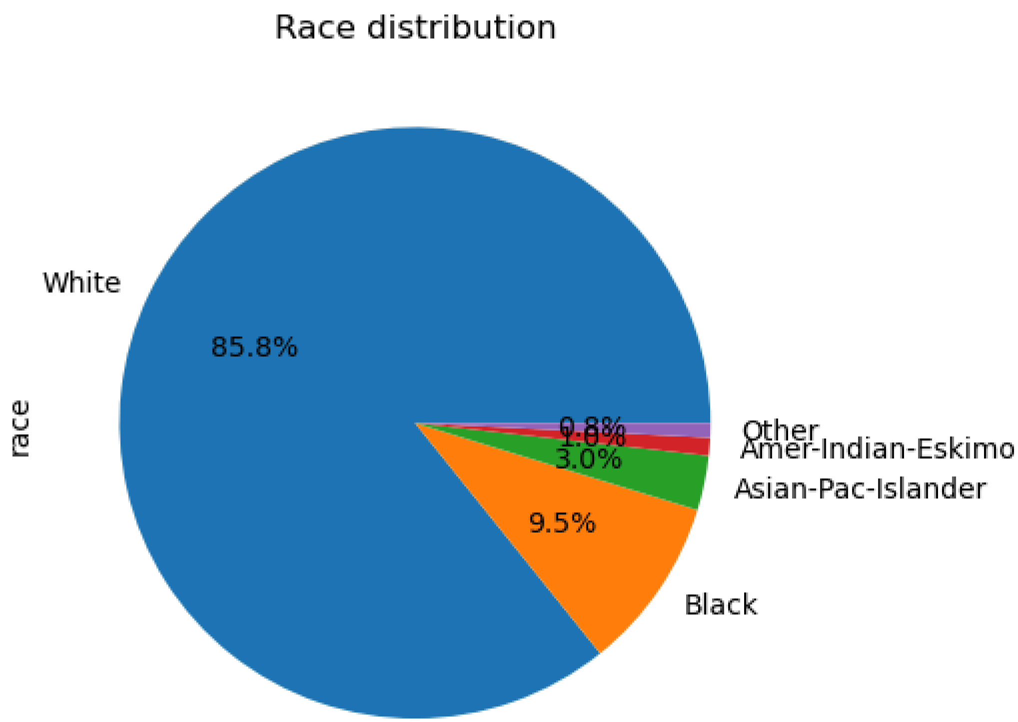
Out[5]:
```
Text(0, 0.5, 'final weight')
```



In [9]:
```
# looks like most observation are within 10-30% of the population.
```

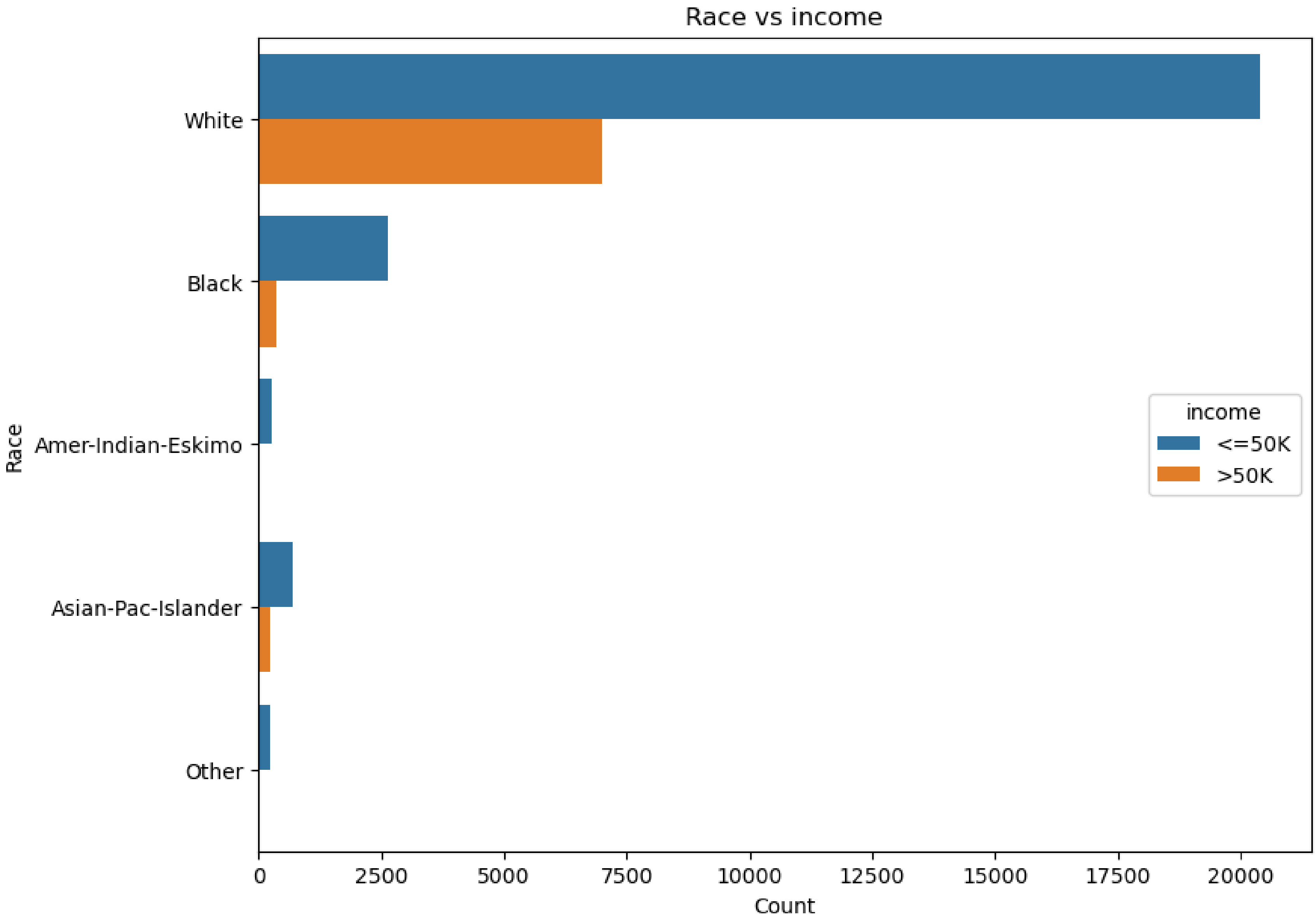
In [6]:
```
# using pie chart to show distribution of the race
data =df.race.value_counts()

data.plot(kind='pie', autopct='%0.1f%%')
plt.title('Race distribution')
```

Out[6]:
```
Text(0.5, 1.0, 'Race distribution')
```



from the pie chart, it is clear that the sampling among races are imbalanced. however per census, 73.6% of us population are white in 1995, so it may reflect the true race distibution of poplulation, not due to a imbalanced sampling.

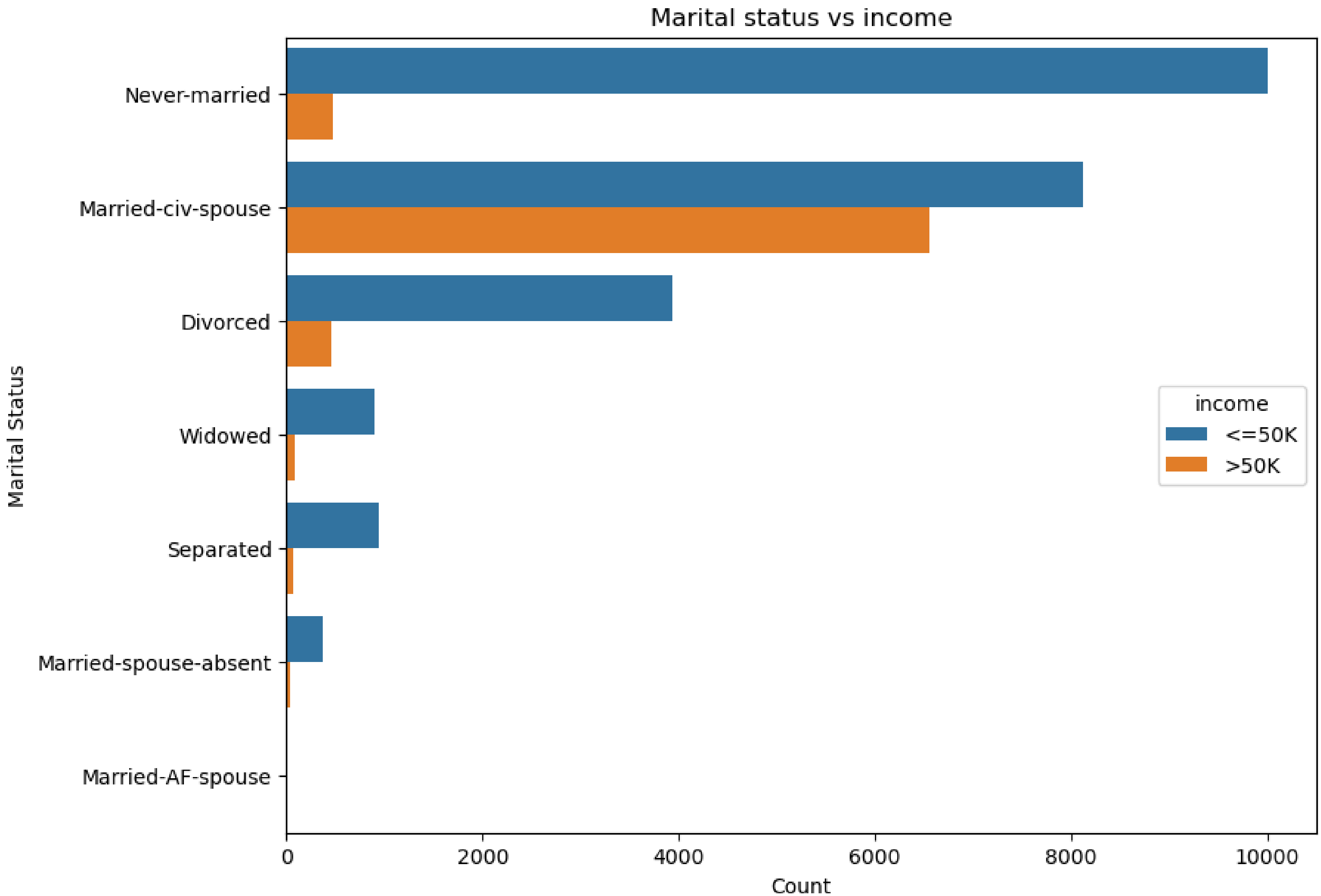
In [11]:
```
# check income based on race (this is new from original milestone 1 submission)
# distribution chart between marital status vs income
plt.figure(figsize=(9,7))
ax = sns.countplot(data=df, y='race', hue='income')

plt.xlabel('Count')
plt.ylabel('Race')
plt.title('Race vs income')

# Add legend
plt.legend
sns.move_legend(ax, "center right")

# Show the plot
plt.show()
```



looks like most data is based on white race, the data from race are limited, the impact of race on income may not have enough data to show

In [18]:
```
# now check relationship between marital status and income
plt.figure(figsize=(9,7))
ax = sns.countplot(data=df, y='marital_status', hue='income')
```

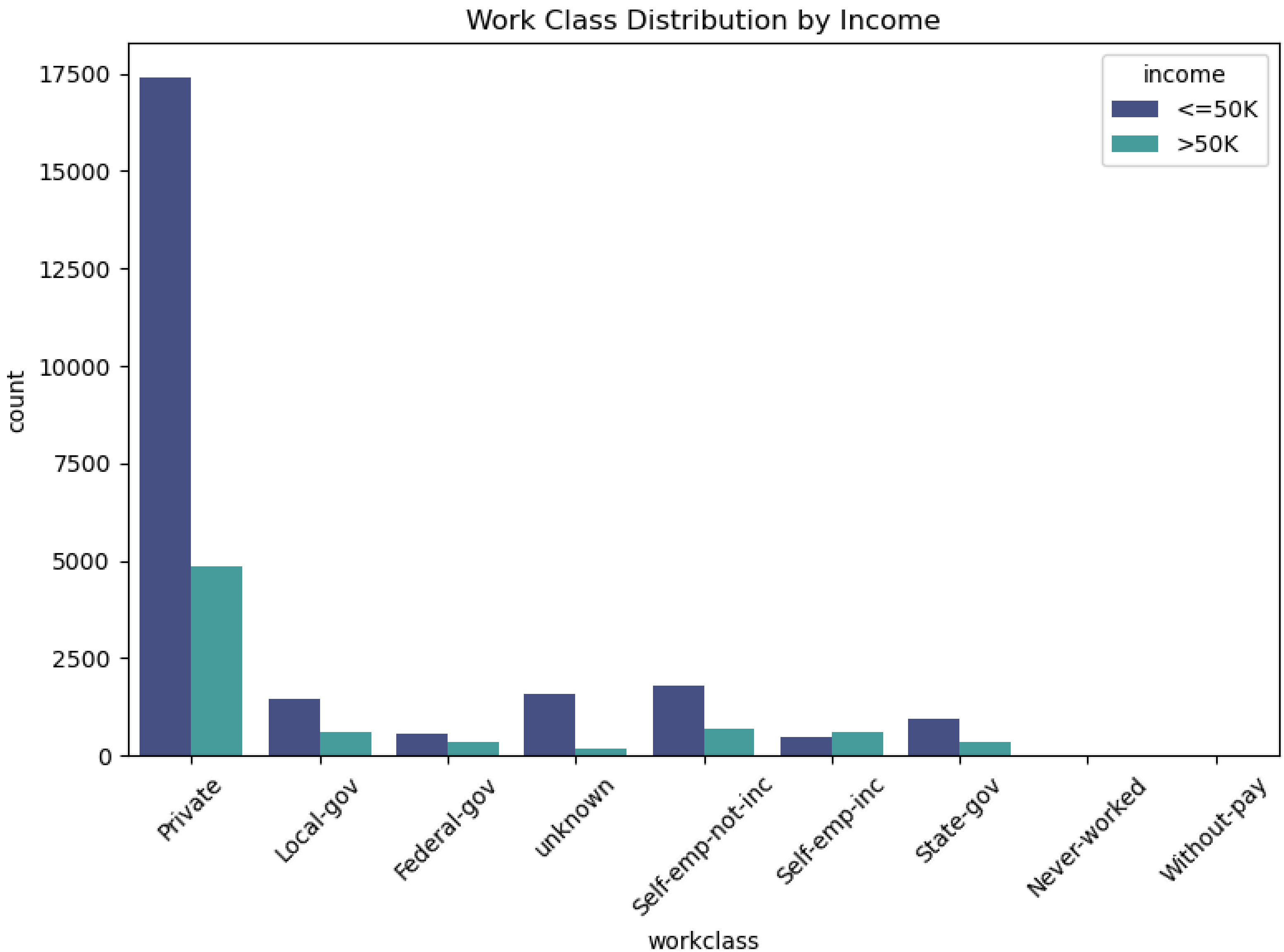
```
plt.xlabel('Count')
plt.ylabel('Marital Status')
plt.title('Marital status vs income')

# Add legend
plt.legend
sns.move_legend(ax, "center right")

# Show the plot
plt.show()
```



From the 2 charts above, looks like there are more data samples on white race, and white earns higher income than any other races. Among the white, the married couple have most chance to have high income (> 50K dollars)

In [19]:
```
# plot work class distribution by income
plt.figure(figsize = (8,6))
sns.countplot(data = df, x = "workclass", hue = "income", palette = "mako")
plt.xticks(rotation = 45)
```

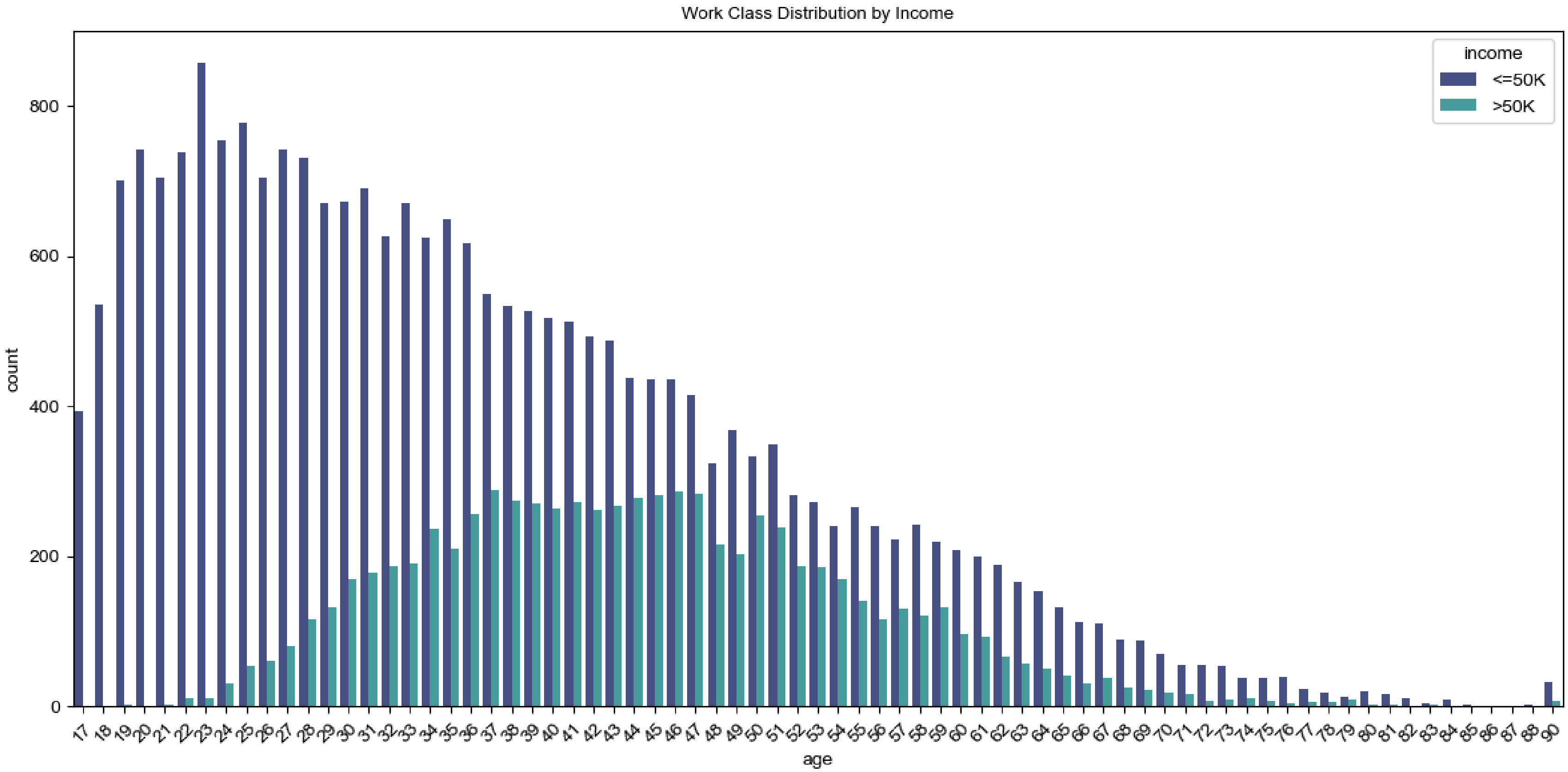
```
plt.title("Work Class Distribution by Income")
plt.tight_layout();
```



From the chart above, private business owner are most likely earn >50K.

In [20]:
```
# plot age distribution by income
plt.figure(figsize = (12,6))
sns.countplot(data = df, x = "age", hue = "income", palette = "mako")
```

```
plt.xticks(rotation = 45)
sns. set(font_scale= 0.8)
plt.title("Work Class Distribution by Income")
plt.tight_layout();
```



from the chart above, high income often show in middle age (age between 30 to 50), also the high income are likely normally distributed based on age, while low income are skewed based on age.

Summary of EDA:

the data has both categorical and numerical variables. so may need some technical skill (like dummy or label) to turn everything into numerical for better anaylysis data has enough variations and variable coverage for model building. Race, marital status, age and workclass have significant impact to income, Correlation analysis could be a necessary step to identify which factors are important and if any factors are correlated. Data is quite clean and ready for model building. This data analysis round could be iternerated, more data distribution and correlation analysis maybe needed during variable selection stage.

2. Data preparation

In [22]:
```
df.head(20)
```

Out[22]:

	age	workclass	fnlwgt	education	education_len	marital_status	occupation	relationship	race	sex	native.country	income
0	17	Private	148522	11th	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
1	17	Private	93235	12th	8	Never-married	occupation	Own-child	White	Female	United-States	<=50K
2	17	Private	184924	9th	5	Never-married	occupation	Own-child	White	Male	United-States	<=50K
3	17	Private	116626	11th	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
4	17	Private	209949	11th	7	Never-married	occupation	Own-child	White	Female	United-States	<=50K
5	17	Private	225106	10th	6	Never-married	occupation	Own-child	White	Female	United-States	<=50K
6	17	Local-gov	170916	10th	6	Never-married	occupation	Own-child	White	Female	United-States	<=50K
7	17	Federal-gov	99893	11th	7	Never-married	occupation	Not-in-family	Black	Female	United-States	<=50K
8	17	Private	218361	10th	6	Never-married	occupation	Own-child	White	Female	United-States	<=50K
9	17	Private	132680	10th	6	Never-married	occupation	Own-child	White	Female	United-States	<=50K
10	17	unknown	304873	10th	6	Never-married	unknown	Own-child	White	Female	United-States	<=50K
11	17	Private	175024	11th	7	Never-married	Handlers-cleaners	Own-child	White	Male	United-States	<=50K
12	17	Private	191260	9th	5	Never-married	Other-service	Own-child	White	Male	United-States	<=50K
13	17	unknown	333100	10th	6	Never-married	unknown	Own-child	White	Male	United-States	<=50K
14	17	Private	103851	11th	7	Never-married	Adm-clerical	Own-child	White	Female	United-States	<=50K
15	17	Private	130125	10th	6	Never-married	Other-service	Own-child	Amer-Indian-Eskimo	Female	United-States	<=50K
16	17	Private	56536	11th	7	Never-married	Sales	Own-child	White	Female	India	<=50K
17	17	Private	191260	11th	7	Never-married	Other-service	Own-child	White	Male	United-States	<=50K
18	17	Private	232713	10th	6	Never-married	Craft-repair	Not-in-family	White	Male	United-States	<=50K
19	17	Private	106733	11th	7	Never-married	Craft-repair	Own-child	White	Male	United-States	<=50K

Data cleanning

In [7]:
```
# there are ''?'' in the 'workclass', 'native.country' and 'education' columns. convert them into 'unknown'
df['workclass'].replace('?', 'unknown', inplace=True)
df['occupation'].replace('?', 'unknown', inplace=True)
df['native.country'].replace('?', 'unknown', inplace=True)
```

In [8]:
```
# education length will reflect education level. so I want to check how useful the education is and drop education colu
df['education'].unique()
```

Out[8]:
```
array(['11th', '12th', '9th', '10th', '5th-6th', 'Some-college',
       'HS-grad', '7th-8th', 'Masters', 'Bachelors', 'Assoc-voc',
       'Assoc-acdm', 'Preschool', '1st-4th', 'Doctorate', 'Prof-school'],
      dtype=object)
```

In [9]:
```
# the 'education length' and 'education' are about the same information, so drop 'deucation' column.
df.drop('education', axis=1, inplace=True)
df.head()
```

Out[9]:

	age	workclass	fnlwgt	education_len	marital_status	occupation	relationship	race	sex	native.country	income
0	17	Private	148522	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
1	17	Private	93235	8	Never-married	occupation	Own-child	White	Female	United-States	<=50K
2	17	Private	184924	5	Never-married	occupation	Own-child	White	Male	United-States	<=50K
3	17	Private	116626	7	Never-married	occupation	Own-child	White	Male	United-States	<=50K
4	17	Private	209949	7	Never-married	occupation	Own-child	White	Female	United-States	<=50K

In [10]:
```
# The data have mixed categorical and numerical data
# now Split our data set into categorical and numerical for data analysis
# from above analysis, the age, fnlwgt and education_len are numerical columns
# the rest columns (workclass, martial_status, income etc.) are categorical
num=df.select_dtypes(include=np.number)
cat=df.select_dtypes(exclude=np.number)
```

In [28]:
```
#check correlation between numerical features and see if any are closely related and can be dropped.
corr = num.corr()
print(corr)
```

```
                    age    fnlwgt  education_len
age            1.000000 -0.076178       0.035951
fnlwgt        -0.076178  1.000000      -0.044539
education_len  0.035951 -0.044539       1.000000
```

the numerical columns are not closely related.

In [11]:

```
# the fnlwgt is a representation of population count, assume it was not quite related to income. so drop it
df.drop('fnlwgt', axis=1, inplace=True)
```

In [12]:

```
# income column and sex are actually binary category, so need to converted to 0 and 1 for future modeling.
def compute_income(x):
  if x=="<=50K":
    return 0
  elif(x=='>50K'):
    return 1

df['income']=df['income'].apply(compute_income)

df['sex']=df['sex'].apply(lambda x : 0 if x=='Male' else 1)

df.head()
```

Out[12]:

	age	workclass	education_len	marital_status	occupation	relationship	race	sex	native.country	income
0	17	Private	7	Never-married	occupation	Own-child	White	0	United-States	0
1	17	Private	8	Never-married	occupation	Own-child	White	1	United-States	0
2	17	Private	5	Never-married	occupation	Own-child	White	0	United-States	0
3	17	Private	7	Never-married	occupation	Own-child	White	0	United-States	0
4	17	Private	7	Never-married	occupation	Own-child	White	1	United-States	0

In [13]:

```
# also notice the occupation has a lot of response as occupation, which is same as no answer, so convert it as unknown.
df['occupation'].replace('occupation', 'unknown', inplace=True)
df.head()
```

Out[13]:

	age	workclass	education_len	marital_status	occupation	relationship	race	sex	native.country	income
0	17	Private	7	Never-married	unknown	Own-child	White	0	United-States	0
1	17	Private	8	Never-married	unknown	Own-child	White	1	United-States	0
2	17	Private	5	Never-married	unknown	Own-child	White	0	United-States	0
3	17	Private	7	Never-married	unknown	Own-child	White	0	United-States	0
4	17	Private	7	Never-married	unknown	Own-child	White	1	United-States	0

Handling the missing values

In [14]:

```
# now we know that workclass, occupation has unknown. so check how many are them
work_unknown = df['workclass'].value_counts()['unknown']
occupation_unknown = df['occupation'].value_counts()['unknown']
print('Ratio of unknown in workclass is', round(work_unknown/len(df['workclass']),2))
print('Ratio of unknown in occupation is', round(occupation_unknown/len(df['occupation']),2))
```

```
Ratio of unknown in workclass is 0.06
Ratio of unknown in occupation is 0.1
```

In [15]:

```
# The ratio of unknown is small so I plan to remove them

df_clean =df[(df.occupation != 'unknown') & (df.workclass != 'unknown')]
df_clean
```

Out[15]:

	age	workclass	education_len	marital_status	occupation	relationship	race	sex	native.country	income
11	17	Private	7	Never-married	Handlers-cleaners	Own-child	White	0	United-States	0
12	17	Private	5	Never-married	Other-service	Own-child	White	0	United-States	0
14	17	Private	7	Never-married	Adm-clerical	Own-child	White	1	United-States	0
15	17	Private	6	Never-married	Other-service	Own-child	Amer-Indian-Eskimo	1	United-States	0
16	17	Private	7	Never-married	Sales	Own-child	White	1	India	0
...	...	...	...	...	...	...	...	...	...	...
31939	90	Private	14	Married-civ-spouse	Prof-specialty	Wife	White	1	United-States	1
31940	90	Private	13	Never-married	Prof-specialty	Not-in-family	Asian-Pac-Islander	0	United-States	0
31943	90	Federal-gov	9	Married-civ-spouse	Craft-repair	Husband	White	0	United-States	0
31944	90	Private	9	Married-civ-spouse	Machine-op-inspct	Husband	White	0	United-States	0
31946	90	Private	9	Widowed	Adm-clerical	Unmarried	White	1	United-States	0

28700 rows × 10 columns

Convert categorical into numerical

Currently the dataframe have mix of numerical and categorical columns, which is hard to use any models I am familar with. I have converted income/sex from binary categories into numerical, I can continue convert rest so I can use prediction model for numerical variables.

In [16]:

```
categorical_cols = ['workclass', 'marital_status', 'occupation', 'relationship', 'race', 'native.country']
newdf = pd.get_dummies(df_clean, columns=categorical_cols, drop_first=True)
newdf
```

Out[16]:

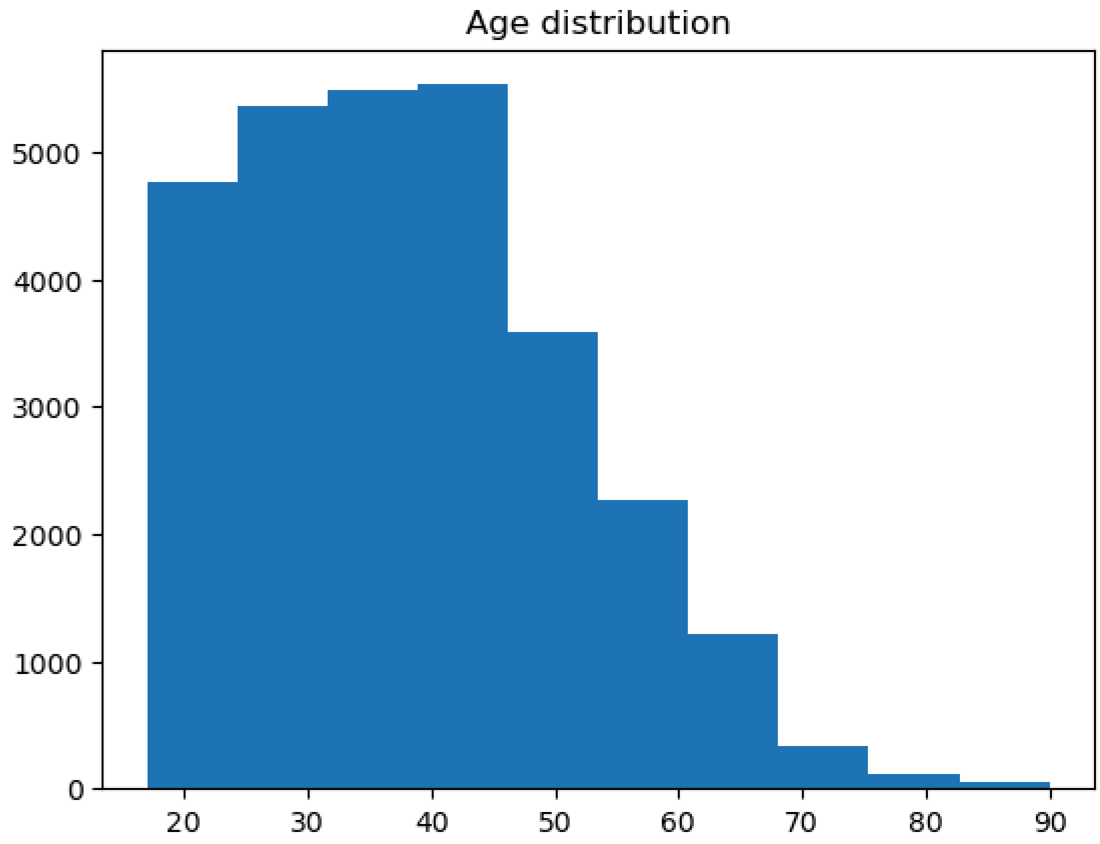
	age	education_len	sex	income	workclass_Local-gov	workclass_Private	workclass_Self-emp-inc	workclass_Self-emp-not-inc	workclass_State-gov	workclass_With
11	17	7	0	0	0	1	0	0	0	
12	17	5	0	0	0	1	0	0	0	
14	17	7	1	0	0	1	0	0	0	
15	17	6	1	0	0	1	0	0	0	
16	17	7	1	0	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	
31939	90	14	1	1	0	1	0	0	0	
31940	90	13	0	0	0	1	0	0	0	
31943	90	9	0	0	0	0	0	0	0	
31944	90	9	0	0	0	1	0	0	0	
31946	90	9	1	0	0	1	0	0	0	

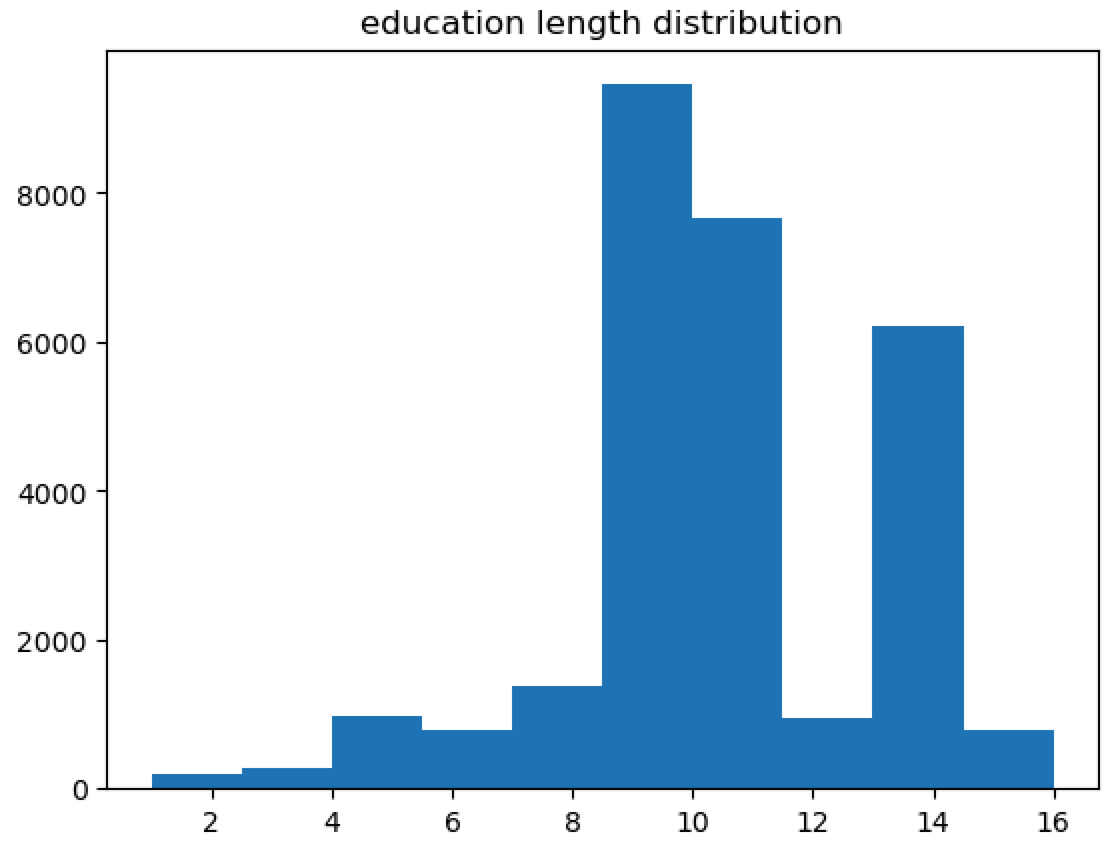
28700 rows × 77 columns

now I have a lot of more columns. all slection choices from each category variables turns into a columns.

In [17]:

```
# now I check distribution of age and education_len to see if they are normal distributed,
#so I can decide if I need to standarlize them

plt.hist(newdf.age)
plt.title('Age distribution')
plt.show()

plt.hist(newdf.education_len)
plt.title('education length distribution')
plt.show()
```


Age distribution
0
1000
2000
3000
4000
5000
20
30
40
50
60
70
80
90



I think the distribution is compact enough so I do not need to standardlize them

3. Building model

Model selection

from last few weeks exercises, I used linear regression model, Polynominal model and Randomforest model for numerical variable prediction. At later weeks, I used support vector Machine model and logical regression for categorical variable predication.

Personally I like random forest since it is a linear regression model but have advantage of overfitting avoid.

I will try random forest regressor first (native one and one with hyperparameter tuning), then I will try Random ForestClassifier model as well

In [18]:
```
# now define the independent features and dependent feature (which is income level)
# load modelling related package
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
import sklearn.metrics as metrics

X = newdf.drop(columns=['income'])
y = newdf.income

#now split it into train and test dataset, 20% are testset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model 1. RandomForest Regressor (native one)

In [19]:
```
from sklearn.ensemble import RandomForestClassifier
#model = RandomForestClassifier(random_state=42)

rf = RandomForestRegressor(n_estimators=300, max_depth=5, random_state=0)
rf.fit(X_train , y_train)
pred = rf.predict(X_test)
pred[4030:4040]
```

Out[19]:
```
array([0.80619507, 0.04137852, 0.04101039, 0.25425958, 0.44838864,
       0.25375449, 0.80550804, 0.01865008, 0.78491931, 0.68162096])
```

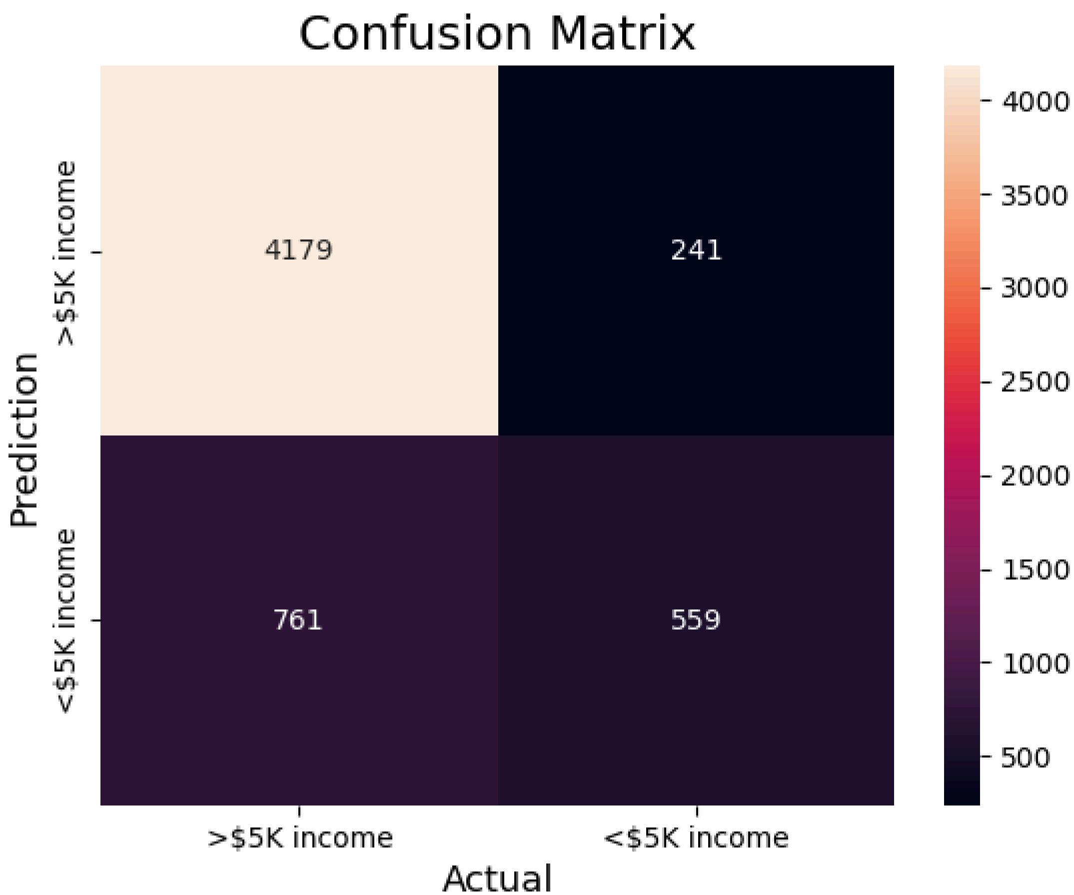
In [20]:
```
# Since the linear regression will return number, so need to convert it to only 0 and 1. use 0.5 as creteria to classify
# >=0.5 will be classified as 1 and <0.5 will be classified as 0
predict =[]
for item in pred:
    if item >= 0.5:
        predict.append(1)
    else:
        predict.append(0)
```

In [21]:
```
from sklearn.metrics import accuracy_score
print('accuracy of native random forest prediction is:',round(accuracy_score(y_test, predict),4))
```

```
accuracy of native random forest prediction is: 0.8254
```

In [22]:
```
# Create a confusion matrix for the test set predictions.

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,predict)
```

```python
#visualize the confusion matrix
import seaborn as sns
import matplotlib.pyplot as plt

sns.heatmap(cm,
            annot=True,
            fmt='g',
            xticklabels=['>$5K income','<$5K income'],
            yticklabels=['>$5K income','<$5K income'])
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



In [23]:
```
# Get the precision, recall, and F1-score for the test set predictions.
from sklearn.metrics import classification_report
print(classification_report(y_test, predict))
```

```
              precision    recall  f1-score   support

           0       0.85      0.95      0.89      4420
           1       0.70      0.42      0.53      1320

    accuracy                           0.83      5740
   macro avg       0.77      0.68      0.71      5740
weighted avg       0.81      0.83      0.81      5740
```

In [25]:
```
#Calculate the R2, RSME and MAE for this model
import sklearn.metrics as metrics
r2_1 = metrics.r2_score(y_test, predict)
mae_1 = metrics.mean_absolute_error(y_test, predict)
mse_1 = metrics.mean_squared_error(y_test, predict)
rmse_1 = np.sqrt(mse_1)

print('R2 value for RF simple is:', r2_1)
print('RSME value for RF simple is:', rmse_1)
print('MAE value for RF simple is:', mae_1)
```

```
R2 value for RF simple is: 0.01421225832990547
RSME value for RF simple is: 0.4178091190128736
MAE value for RF simple is: 0.17456445993031358
```

Model 2. RandomForest Regressor (with hyper parameter optimizer)

In [26]:
```
model2 = RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
}
```

In [27]:
```
# use hyperparameter tuning
from sklearn.model_selection import GridSearchCV
grid_search_rf = GridSearchCV(model2, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid_search_rf.fit(X, y)
```

Out[27]:

```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [28]:

```
# find out best estimator
best_RF_model = grid_search_rf.best_estimator_
y_pred_rf=best_RF_model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred_rf)
```

In [29]:

```
print("random forest regression with hyperparameter tuning Accuracy:", round(accuracy,4))
```

```
random forest regression with hyperparameter tuning Accuracy: 0.835
```

model 2 is very computer resource consuming but improved the accuracy by 0.01

In [31]:

```
#Calculate the R2, RSME and MAE for second model
import sklearn.metrics as metrics
r2_2 = metrics.r2_score(y_test, y_pred_rf)
mae_2 = metrics.mean_absolute_error(y_test, y_pred_rf)
mse_2 = metrics.mean_squared_error(y_test, y_pred_rf)
rmse_2 = np.sqrt(mse_1)

print('R2 value for RF simple is:', r2_2)
print('RSME value for RF simple is:', rmse_2)
print('MAE value for RF simple is:', mae_2)
```

```
R2 value for RF simple is: 0.06832236391059932
RSME value for RF simple is: 0.4178091190128736
MAE value for RF simple is: 0.16498257839721253
```

In [32]:

```
# Get the precision, recall, and F1-score for the test set predictions.
print(classification_report(y_test, y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.85      0.95      0.90      4420
           1       0.74      0.44      0.55      1320

    accuracy                           0.84      5740
   macro avg       0.79      0.70      0.72      5740
weighted avg       0.82      0.84      0.82      5740
```

the 2 models are comparable in term of accruacy and other performance indicators.

Classifier: RandomForestClassifier model

In [53]:
```
# data prediction using classifier

from sklearn.ensemble import RandomForestClassifier
cf = RandomForestClassifier(random_state=42)
cf.fit(X_train, y_train)
```

Out[53]:
```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

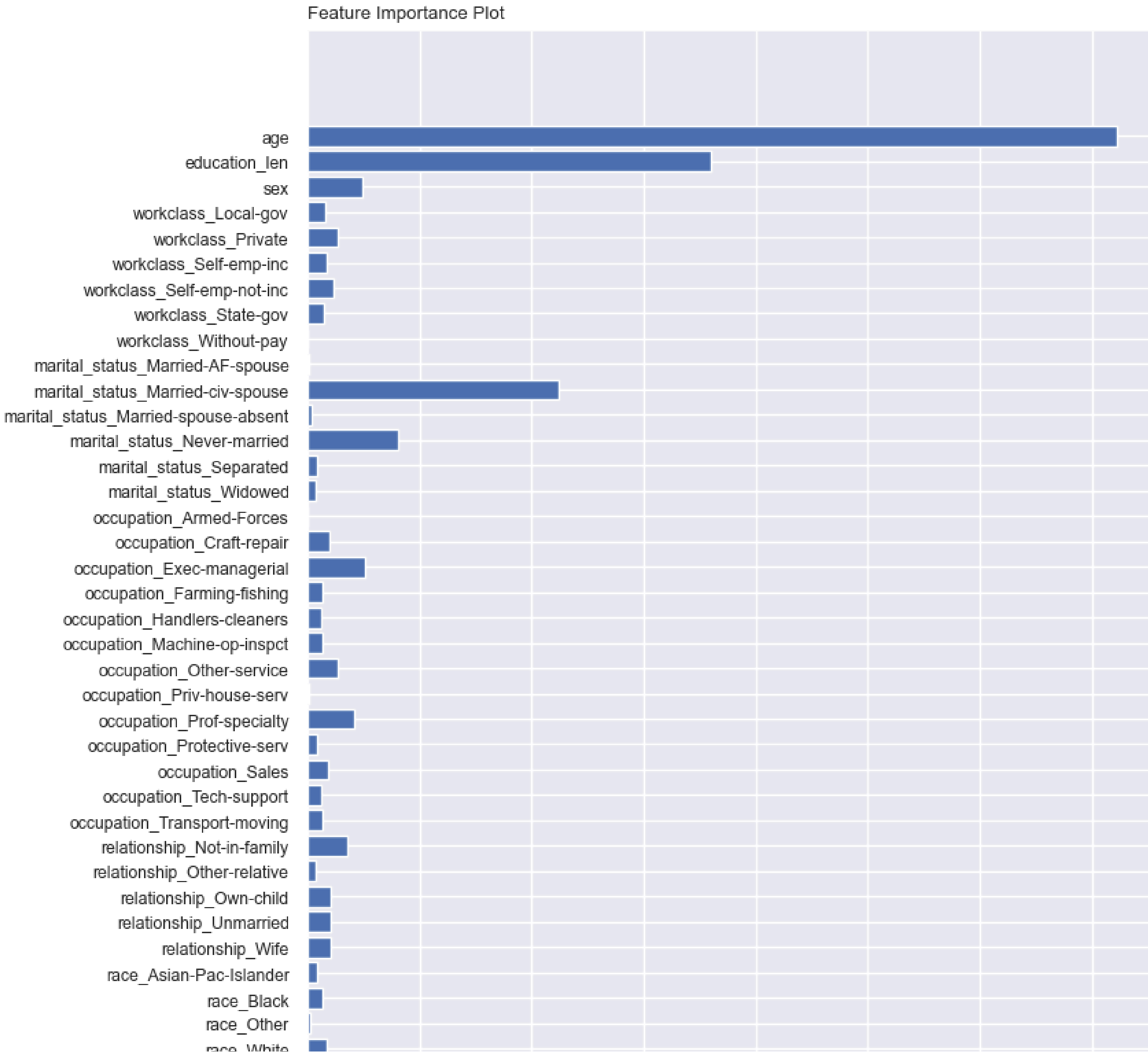
In [54]:
```
# make prediction
cf_y_pred = cf.predict(X_test)
```

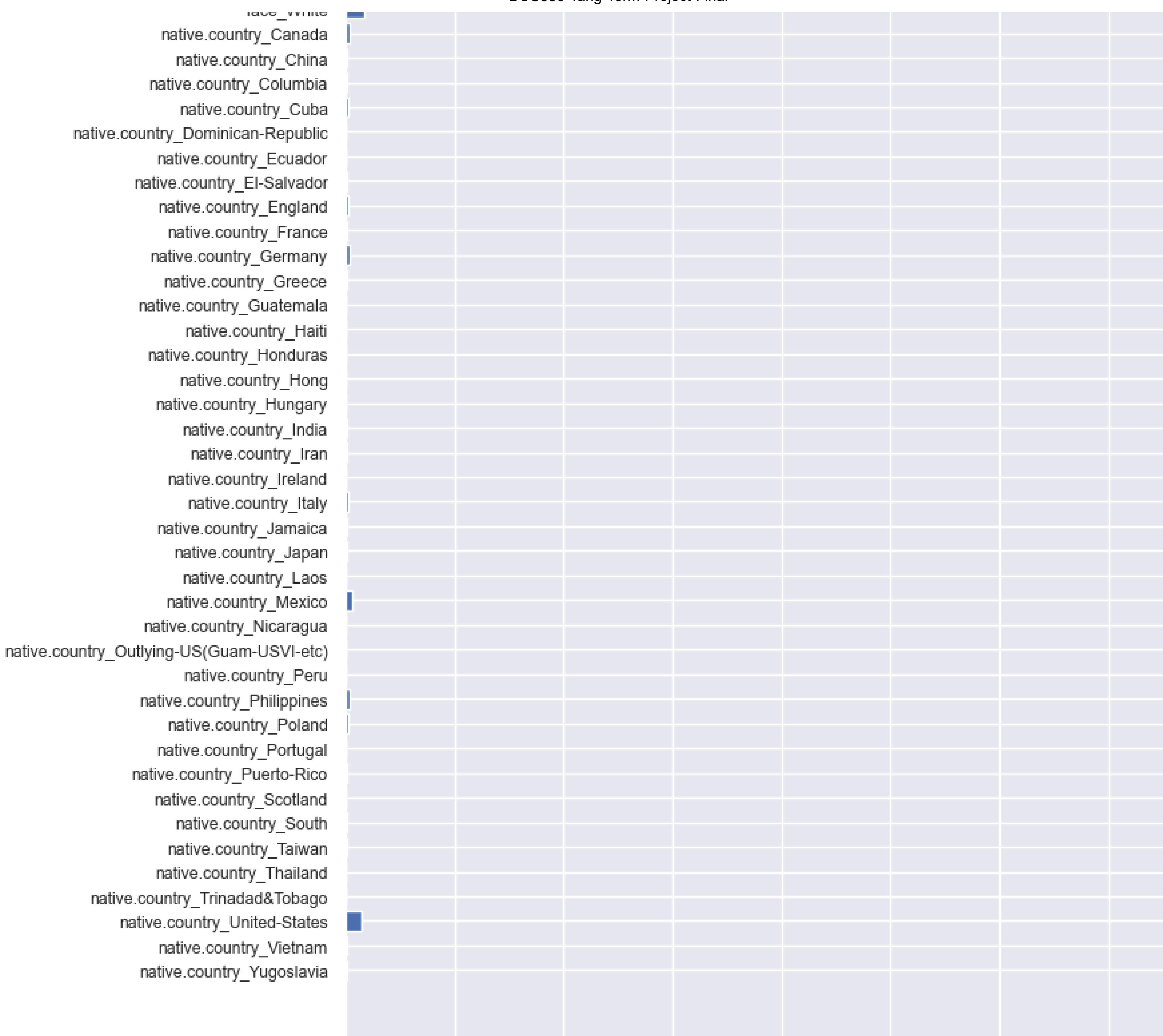
In [55]:
```
print(f'Accuracy of classifier is:', round(accuracy_score(y_test, cf_y_pred), 4))
```

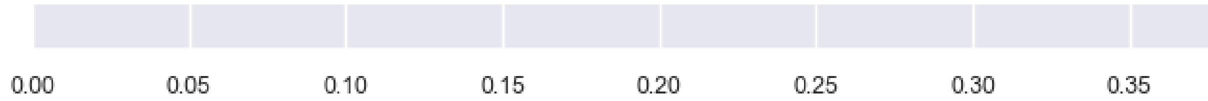
```
Accuracy of classifier is: 0.8061
```

In [56]:
```
# Calculate feature importance
feature_importances = cf.feature_importances_
```

In [58]:
```
# try plot again
fig, ax = plt.subplots(figsize =(8, 20))

ax.barh(X_train.columns, feature_importances )

ax.invert_yaxis()

ax.set_title('Feature Importance Plot',loc ='left', )

plt.show()
```


Feature Importance Plot
age
education_len
sex
workclass_Local-gov
workclass_Private
workclass_Self-emp-inc
workclass_Self-emp-not-inc
workclass_State-gov
workclass_Without-pay
marital_status_Married-AF-spouse
marital_status_Married-civ-spouse
marital_status_Married-spouse-absent
marital_status_Never-married
marital_status_Separated
marital_status_Widowed
occupation_Armed-Forces
occupation_Craft-repair
occupation_Exec-managerial
occupation_Farming-fishing
occupation_Handlers-cleaners
occupation_Machine-op-inspct
occupation_Other-service
occupation_Priv-house-serv
occupation_Prof-specialty
occupation_Protective-serv
occupation_Sales
occupation_Tech-support
occupation_Transport-moving
relationship_Not-in-family
relationship_Other-relative
relationship_Own-child
relationship_Unmarried
relationship_Wife
race_Asian-Pac-Islander
race_Black
race_Other


native.country_Canada
native.country_China
native.country_Columbia
native.country_Cuba
native.country_Dominican-Republic
native.country_Ecuador
native.country_El-Salvador
native.country_England
native.country_France
native.country_Germany
native.country_Greece
native.country_Guatemala
native.country_Haiti
native.country_Honduras
native.country_Hong
native.country_Hungary
native.country_India
native.country_Iran
native.country_Ireland
native.country_Italy
native.country_Jamaica
native.country_Japan
native.country_Laos
native.country_Mexico
native.country_Nicaragua
native.country_Outlying-US(Guam-USVI-etc)
native.country_Peru
native.country_Philippines
native.country_Poland
native.country_Portugal
native.country_Puerto-Rico
native.country_Scotland
native.country_South
native.country_Taiwan
native.country_Thailand
native.country_Trinadad&Tobago
native.country_United-States
native.country_Vietnam
native.country_Yugoslavia



looks like age and education length are the 2 most important factors. married with spouse living together can improve the income level as well. occupation matters a little. Native country may not have enough data to tell the difference.

The classifier gives a visualization of the important factors and also the strength of each factor.

End words: this book is to record coding only, please refer to the summary report in word for project report out.

In [ ]:

```

```