Census Income Machine Learning Project

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import dataset

In [1]:
```
import pandas as pd
df = pd.read_csv('adult.data',na_values=[' ?'])
print(df.head())
print('\nDimensions of data frame:', df.shape)
```

```
   39          State-gov   77516   Bachelors   13        Never-married  \
0  50   Self-emp-not-inc   83311   Bachelors   13   Married-civ-spouse
1  38            Private  215646     HS-grad    9             Divorced
2  53            Private  234721        11th    7   Married-civ-spouse
3  28            Private  338409   Bachelors   13   Married-civ-spouse
4  37            Private  284582     Masters   14   Married-civ-spouse

         Adm-clerical   Not-in-family   White     Male   2174   0   40  \
0     Exec-managerial         Husband   White     Male      0   0   13
1   Handlers-cleaners   Not-in-family   White     Male      0   0   40
2   Handlers-cleaners         Husband   Black     Male      0   0   40
3      Prof-specialty            Wife   Black   Female      0   0   40
4     Exec-managerial            Wife   White   Female      0   0   40

    United-States   <=50K
0   United-States   <=50K
1   United-States   <=50K
2   United-States   <=50K
3            Cuba   <=50K
4   United-States   <=50K

Dimensions of data frame: (32560, 15)
```

This is a dataset containing census information on adults including income and other related attributes. The dataset can be found at: https://archive.ics.uci.edu/ml/datasets/Adult (https://archive.ics.uci.edu/ml/datasets/Adult)

Data Cleaning

Give dataset columnnames and drop N/A rows

In [2]:
```
df.columns = ['age','class','fnlwgt','education','eduNum','marital-status',
              'ocupation','relationship','race','sex','capitalGain',
              'capitalLoss','hours','nativeCountry','income']
df.describe()
df = df.dropna()
print('\nDimensions of data frame:', df.shape)
```

```
Dimensions of data frame: (30161, 15)
```

Convert columns to categorical data type

In [3]:
```
df["class"] = df["class"].astype('category')
df["education"] = df["education"].astype('category')
df["marital-status"] = df["marital-status"].astype('category')
df["ocupation"] = df["ocupation"].astype('category')
df["relationship"] = df["relationship"].astype('category')
df["race"] = df["race"].astype('category')
df["sex"] = df["sex"].astype('category')
df["nativeCountry"] = df["nativeCountry"].astype('category')
df["income"] = df["income"].astype('category')
print(df.dtypes)
```

```
age                  int64
class             category
fnlwgt               int64
education         category
eduNum               int64
marital-status    category
ocupation         category
relationship      category
race              category
sex               category
capitalGain          int64
capitalLoss          int64
hours                int64
nativeCountry     category
income            category
dtype: object
```

Data Exploration

Here are a few functions that are useful in seeing disparity among classes of people in America.

Percentages of Races

In [4]:
```
print([(race,count/len(df['race'])) for (race,count) in
       list(zip(df.race.value_counts().index,df.race.value_counts()))])
```

```
[(' White', 0.8597858161201551), (' Black', 0.09339875998806406), (' Asian-Pac-Islander',
0.0296740824243228), (' Amer-Indian-Eskimo', 0.009482444216040583), (' Other', 0.00765889
7251417393)]
```

Odds of a african american person making over 50k

In [5]:
```
print(len(df[((df['race'].eq(' Black')) & (df['income'].eq(' >50K')))])
      /len(df[(df['race'].eq(' Black'))]))
```

```
0.1299254526091587
```

Odds of a white person making over 50k

In [6]:
```
print(len(df[((df['race'].eq(' White')) & (df['income'].eq(' >50K')))])
      /len(df[(df['race'].eq(' White'))]))
```

```
0.2637282122474163
```

Odds of a white male making over 50k

In [7]:
```
print(len(df[((df['race'].eq(' White')) & (df['sex'].eq(' Male'))
              & (df['income'].eq(' >50K')))])/len(df[(df['race'].eq(' White'))
              & (df['sex'].eq(' Male'))]))
```

```
0.32533126351388814
```

Odds of a african american female making over 50k

In [8]:
```
print(len(df[((df['race'].eq(' Black')) & (df['sex'].eq(' Female'))
              & (df['income'].eq(' >50K')))])/len(df[(df['race'].eq(' Black'))
              & (df['sex'].eq(' Female'))]))
```

```
0.06075768406004289
```

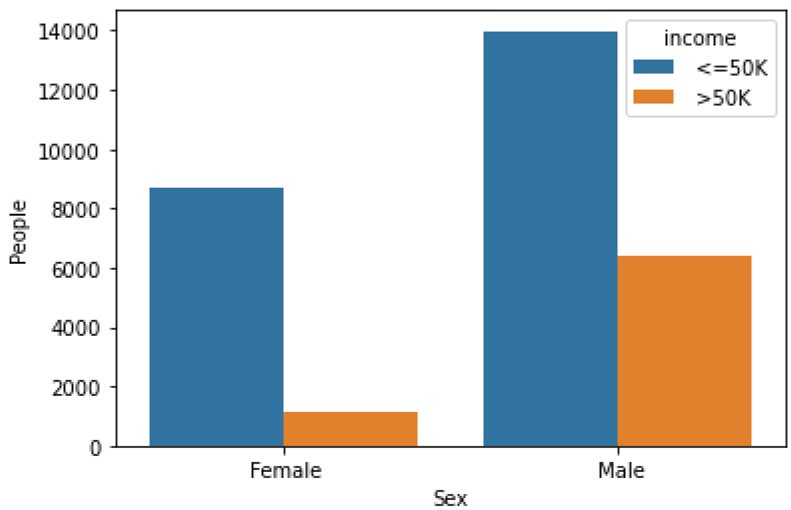
Data Visualization

From our created plot we can infer which predictors will give us good insight into someone's income. Usually a correlation plot provides good insight into our predictors but because our attributes are mainly categorical it is harder to interpret any correlation especially for attributes with narrow ranges.

In [9]:
```
import seaborn as sb
import matplotlib.pyplot as plt
#get copy of dataframe so we can get category codes for our correlation plot
corrDF = df.copy()
#correlation plot requires plottable data thats not string named
corrDF['race'] = corrDF['race'].astype("category").cat.codes
corrDF['sex'] = corrDF['sex'].astype("category").cat.codes
corrDF['age'] = corrDF['age'].astype("category").cat.codes
corrDF['education'] = corrDF['education'].astype("category").cat.codes
corrDF['nativeCountry'] = corrDF['nativeCountry'].astype("category").cat.codes
g = sb.pairplot(corrDF,vars=['race','sex','age','education','nativeCountry'], hue="income"
```

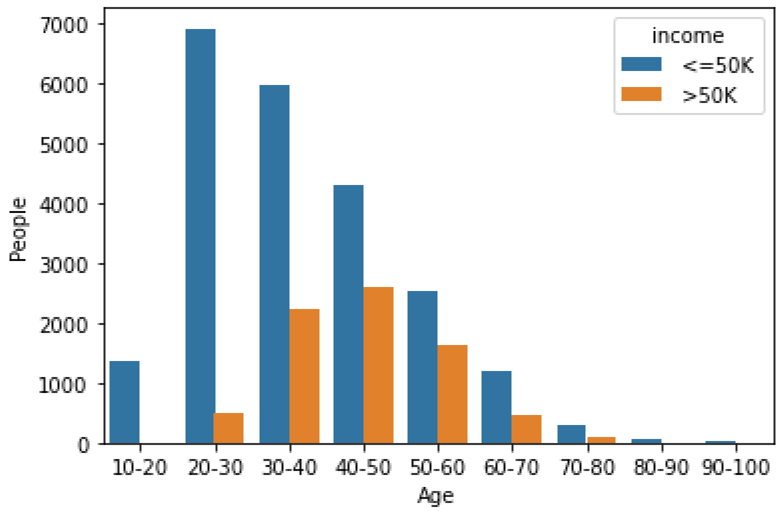
In [10]:
```
ax = sb.countplot(x='sex', hue="income", data=df)
ax.set(xlabel='Sex', ylabel='People')
```

Out[10]:
```
[Text(0, 0.5, 'People'), Text(0.5, 0, 'Sex')]
```

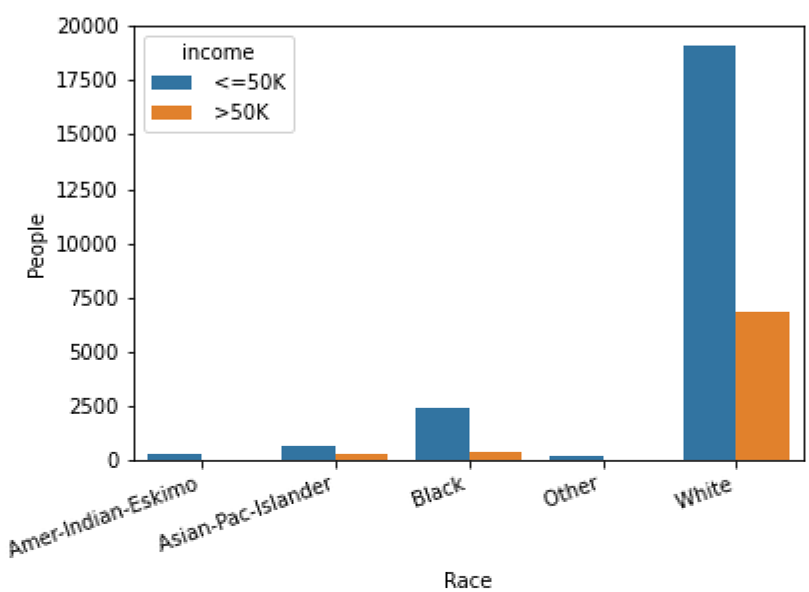


In [11]:
```
import math

#create new series of age group from converted ages
df['ageGroup'] = [str(math.floor(x/10)*10)+"-"+str((math.floor(x/10)*10)+10) for x in df['a
#set to category dtype
df["ageGroup"] = df["ageGroup"].astype('category')

#create frquency plot
ax = sb.countplot(x='ageGroup', hue="income", data=df)
ax.set(xlabel='Age', ylabel='People')
```

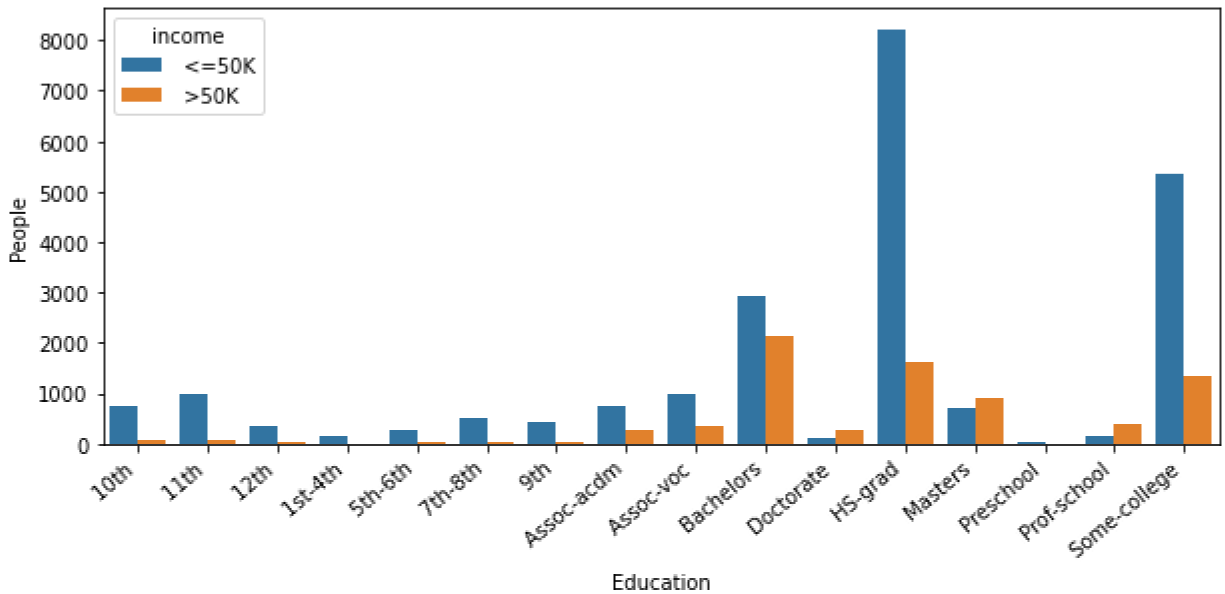
Out[11]:
```
[Text(0, 0.5, 'People'), Text(0.5, 0, 'Age')]
```



In [12]:
```
ax = sb.countplot(x='race', hue="income", data=df)
#rotate tick labels
ax.set_xticklabels(ax.get_xticklabels(), rotation=20, ha="right")
ax.set(xlabel='Race', ylabel='People')
plt.show()
```



In [13]:
```
#resize table to fit tick labels
plt.figure(figsize=(10,4))
ax = sb.countplot(x='education', hue="income", data=df)
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right")
ax.set(xlabel='Education', ylabel='People')
plt.show()
```



Machine Learning Algorithms

Convert predictors to trainable data and split into test and train sets

In [14]:
```
from sklearn.model_selection import train_test_split
df['race'] = df['race'].astype("category").cat.codes
df['sex'] = df['sex'].astype("category").cat.codes
df['age'] = df['age'].astype("category").cat.codes
df['education'] = df['education'].astype("category").cat.codes
df['relationship'] = df['relationship'].astype("category").cat.codes
X = df.loc[:,['education','age','race','sex','relationship']]
y = df.loc[:,['income']]
(X_train, X_test, y_train, y_test) = train_test_split(X, y, test_size=0.2, random_state=12
print('train size:', X_train.shape)
print('test size:', X_test.shape)
```

```
train size: (24128, 5)
test size: (6033, 5)
```

Perform algorithms on test data and save metrics

In [15]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confus

models = [ ('LogReg', LogisticRegression()),
           ('NaiveB', MultinomialNB()),
           ('kNN', KNeighborsClassifier(n_neighbors=5)),
           ('DTree', DecisionTreeClassifier()),
           ('RForest',RandomForestClassifier(n_estimators=100, bootstrap = True)) ]

clf_acc = {}
clf_precision = {}
clf_recall = {}
clf_f1 = {}

print('Confusion Matrices:')
for (clf, model) in models:
    model.fit(X_train, y_train.values.ravel())
    y_pred = model.predict(X_test)
    print(clf+':\n',confusion_matrix(y_test, y_pred))
    clf_acc[clf] = accuracy_score(y_test, y_pred)
    clf_precision[clf] = precision_score(y_test, y_pred, pos_label=' >50K')
    clf_recall[clf] = recall_score(y_test, y_pred, pos_label=' >50K')
    clf_f1[clf] = f1_score(y_test, y_pred, pos_label=' >50K')
```

```
Confusion Matrices:
LogReg:
 [[4354  208]
 [1289  182]]
NaiveB:
 [[3506 1056]
 [ 689  782]]
kNN:
 [[4064  498]
 [ 704  767]]
DTree:
 [[4112  450]
 [ 671  800]]
RForest:
 [[4093  469]
 [ 651  820]]
```

Print Metrics for each algorithm

In [16]:
```
for clf in clf_acc:
    print(clf, 'Acc:\t', clf_acc[clf])
print()
for clf in clf_precision:
    print(clf, 'Prec:\t', clf_precision[clf])
print()
for clf in clf_recall:
    print(clf, 'Recall:\t', clf_recall[clf])
print()
for clf in clf_f1:
    print(clf, 'F1:   \t', clf_f1[clf])
```

```
LogReg Acc:      0.7518647439085032
NaiveB Acc:      0.7107575004143876
kNN Acc:         0.8007624730648102
DTree Acc:       0.8141886292060335
RForest Acc:     0.8143543842201226

LogReg Prec:     0.4666666666666667
NaiveB Prec:     0.42546245919477693
kNN Prec:        0.6063241106719368
DTree Prec:      0.64
RForest Prec:    0.6361520558572537

LogReg Recall:   0.12372535690006799
NaiveB Recall:   0.5316111488783141
kNN Recall:      0.521414004078858
DTree Recall:    0.5438477226376615
RForest Recall:  0.557443915703603

LogReg F1:       0.1955937667920473
NaiveB F1:       0.47265034753702023
kNN F1:          0.5606725146198831
DTree F1:        0.5880191106210952
RForest F1:      0.5942028985507246
```

Results Analysis

The algorithm that scored the best as seen below was Random Forest. This makes since due to it being an ensemble method as it gets to aggregate the best performing trees it generates. As we can see it did not perform that much better even though it generated 100 random Decision Trees.

The runner up algorithm the performed similar to Random Forest was Decision Tree. Most of our predictors fed into our models were categorical data which Decision Tree was able to easily create accurate branches on.

Our next best algorithm was kNN which usually performs well on train data, but for this particular set of data was somewhat suprising. Since the predictors we selected had small range of categorical values. Besides this limited input kNN was still able to group targets together very well.

Logistic Regression and NaiveBayes performed significantly worse than the other two.

This script was able to build models to predict someones income based on only 4 predictors such as race, age, sex, and education. This can be used in marketing to target, for examples advertising certain cars based on what they are most likely to afford. The script also shows results of how a persons circumstances can affect their odds of making over 50k.

In [17]:
```
print('Best Model Accuracy Score:\t',max([(score,clf)
            for (clf,score) in clf_acc.items()])[1])
print('Best Model Pecision Score:\t',max([(score,clf)
            for (clf,score) in clf_precision.items()])[1])
print('Best Model Recall Score:  \t',max([(score,clf)
            for (clf,score) in clf_recall.items()])[1])
print('Best Model F1 Score:      \t',max([(score,clf)
            for (clf,score) in clf_f1.items()])[1])
```

```
Best Model Accuracy Score:       RForest
Best Model Pecision Score:       DTree
Best Model Recall Score:         RForest
Best Model F1 Score:             RForest
```

Python vs. R

I prefer python over R because I am able to use my programming skills in python a lot more than R. R does not seem to be a good language programming wise. I can see the benifits of both, but for me python offers alot more machine learning by automating the many parts of our script. Machine learning in python I think tends to make things side on the Computer Science branch of machine learning rather that the Statistics side because it is a more developed programming language.

TLDR: R had a lot more built in functionality that was geared towards statistics, but python seems more powerful when it comes to machine learning.