# Adult Census Salary

February 22, 2020

## 1 Adult Census Salary Dataset - PyMongo

This Machine Learning analyses friendly Adult Census Income dataset, provided by UCI. It is used to model an income classification system to predict whether income exceeds $50K per annum based on census data. The data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker (Data Mining and Visualization, Silicon Graphics).

#### 1.0.1 Data Setup

[176]:
```
# for python interpreter
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

[177]:
```
# import block

import pymongo # pymongo package to connect with mongodb
from pymongo import MongoClient
import pprint #for pretty printing
import re
import warnings
warnings.simplefilter('ignore')
```

[178]:
```
# to connect to MongoClient localhost
client = MongoClient('localhost', 27017)
```

[179]:
```
# database 'assignments' and dataset 'adultcensus' being selected

db = client['assignments']
collection = db['adultcensus']
cur_adultcensus = collection.find()
```

#### 1.0.2 MongoDB Queries

[180]:
```
# to check document count
total = collection.count_documents({})
print("Total document count in the collection is ", total)
```

```
Total document count in the collection is  32561
```

[181]:
```python
# for loop to iterate through the documents in the cursor
# limit(1) to display a single record to understand schema
for doc in collection.find().limit(1):
    pprint.pprint (doc)
```

```
{'_id': ObjectId('5e4a23cd61c3cdf1528a4508'),
 'age': 90,
 'capital_gain': 0,
 'capital_loss': 4356,
 'education': 'HS-grad',
 'education_num': 9,
 'fnlwgt': 77053,
 'hours_per_week': 40,
 'income': '<=50K',
 'marital_status': 'Widowed',
 'native_country': 'United-States',
 'occupation': '?',
 'race': 'White',
 'relationship': 'Not-in-family',
 'sex': 'Female',
 'workclass': '?'}
```

[182]:
```python
# Query 1 - Distinct entries of education, occupation, & workclass
# to understand the dataset

db.adultcensus.distinct("education")
db.adultcensus.distinct("occupation")
db.adultcensus.distinct("workclass")
```

[182]:
```
['10th',
 '11th',
 '12th',
 '1st-4th',
 '5th-6th',
 '7th-8th',
 '9th',
 'Assoc-acdm',
 'Assoc-voc',
 'Bachelors',
 'Doctorate',
 'HS-grad',
 'Masters',
 'Preschool',
 'Prof-school',
 'Some-college']
```

[182]: ['?',
```
 'Adm-clerical',
 'Armed-Forces',
 'Craft-repair',
 'Exec-managerial',
 'Farming-fishing',
 'Handlers-cleaners',
 'Machine-op-inspct',
 'Other-service',
 'Priv-house-serv',
 'Prof-specialty',
 'Protective-serv',
 'Sales',
 'Tech-support',
 'Transport-moving']
```

[182]: ['?',
```
 'Federal-gov',
 'Local-gov',
 'Never-worked',
 'Private',
 'Self-emp-inc',
 'Self-emp-not-inc',
 'State-gov',
 'Without-pay']
```

[183]:
```
# Query 2 - The dataset is skewed towards people with native country as the US
# In the given dataset people with the US as their native country has close to␣
 ↪90% share,
# it is certainly due to the higher proportion of the people native to the US.
# The query aggregate documents by native_country, calculates counts and␣
 ↪percentage respectively.


pipe =     [{ "$group" : {
                "_id" : "$native_country",
                "count" : { "$sum" : 1}}},
        { "$sort" : {"count" : -1 } },
        { "$limit" : 10 },
        {"$project" : {
                "count" : "$count",
                "percentage" : { "$concat" : [{ "$substr" : [{
                                    "$multiply" : [{ "$divide" : [
                                                "$count", total]}, 100]},␣
 ↪0,4]}, "", "%"]}}}}]
# store results in a cursor
cursor = collection.aggregate(pipeline = pipe)
```

```
# for loop to iterate through the documents in the cursor
for doc in cursor:
    pprint.pprint(doc)
```

```
{'_id': 'United-States', 'count': 29170, 'percentage': '89.5%'}
{'_id': 'Mexico', 'count': 643, 'percentage': '1.97%'}
{'_id': '?', 'count': 583, 'percentage': '1.79%'}
{'_id': 'Philippines', 'count': 198, 'percentage': '0.60%'}
{'_id': 'Germany', 'count': 137, 'percentage': '0.42%'}
{'_id': 'Canada', 'count': 121, 'percentage': '0.37%'}
{'_id': 'Puerto-Rico', 'count': 114, 'percentage': '0.35%'}
{'_id': 'El-Salvador', 'count': 106, 'percentage': '0.32%'}
{'_id': 'India', 'count': 100, 'percentage': '0.30%'}
{'_id': 'Cuba', 'count': 95, 'percentage': '0.29%'}
```

[184]:
```
# Query 3 - females seems to earn 50K+ salary early than males
# The aggregation query compares minimum, maximum, and average age for male and
 ↪female who earns more than 50K.
# The average age of females who makes more than 50K is less than that of males.


pipe = [{ "$match" : { "income" : {
                    "$eq" : ">50K"}}},
        { "$group" : {
                "_id" : "$sex",
                "Min_Age" : { "$min" : "$age"},
                "Max_Age" : { "$max" : "$age"},
                "Avg_Age" : { "$avg" : "$age"}
            }}]

# store results in a cursor
cur = collection.aggregate(pipeline = pipe)

# for loop to iterate through the documents in the cursor
for doc in cur:
    pprint.pprint(doc)
```

```
{'Avg_Age': 42.125530110262936, 'Max_Age': 90, 'Min_Age': 19, '_id': 'Female'}
{'Avg_Age': 44.62578805163614, 'Max_Age': 90, 'Min_Age': 19, '_id': 'Male'}
```

[185]:
```
# bucket aggregation example
# Query 5 - Young Adults age group (18-34) dominates in the 50K+ salary
 ↪distribution
# This bucket query categorizes the documents in various age groups,
# namely -  Teen: 0-17, Young adults: 18-34, Adults:35-49, and Elderly 50+.
```

```
# It depicts the percentage of people in the age groups who earns more than 50K.
↪
# It is evident that Young Adults: 18-34 have the highest proportion of more␣
↪than half.


total_50k = 0
for doc in collection.find({"income": ">50K"}):
    total_50k =  total_50k + 1

import math
pipe =    [
        { "$match" : { "income" : {"$eq" : ">50K"}}},
        { "$bucket" : {"groupBy" : "$age",
                "boundaries" : [0, 18, 35, 50, 100],
                "output" : { "count" : { "$sum" : 1.0}}}},
        { "$project" : {"total" : "$sum",
                "% >50K" : { "$concat" : [
                        { "$substr" : [{ "$multiply" : [ { "$divide" :␣
↪["$count", total_50k]},
                                            100] }, 0, 4]}, "", "%"]}}}}]
# store results in a cursor
cur = collection.aggregate(pipeline = pipe)

# for loop to iterate through the documents in the cursor
for doc in cur:
    pprint.pprint(doc)
```

```
{'% >50K': '18.9%', '_id': 18}
{'% >50K': '50.9%', '_id': 35}
{'% >50K': '30.0%', '_id': 50}
```

[186]:

```
# mapReduce example PyMongo
# Query 6 (map reduce) - bachelor degree tops the chart
# Top 5 education according to count of people who earns more than $50K.
# Majority of the people who earns 50K+ completed a bachelor degree and it is␣
↪followed by HS-grad.


from bson.code import Code
mapFunction = Code("""function() {
                                    emit(this.education,1);}""")

reduceFunction = Code("""function(key, values) {
                                                sum = Array.sum(values);
                                                return sum  }""")
```

```
# store results in a cursor, a new collection name education_50k will be reated␣
↪in mongodb
cur = collection.map_reduce( mapFunction, reduceFunction,
                             "education_50k" , query={"income": ">50K"})

# for loop to iterate through the documents in the cursor
for doc in cur.find(sort=[("value", pymongo.DESCENDING)]).limit(5):
    pprint.pprint (doc)
```

```
{'_id': 'Bachelors', 'value': 2221.0}
{'_id': 'HS-grad', 'value': 1675.0}
{'_id': 'Some-college', 'value': 1387.0}
{'_id': 'Masters', 'value': 959.0}
{'_id': 'Prof-school', 'value': 423.0}
```

[187]:
```
# mapReduce example PyMongo
# Query 7 (map reduce) - Asian-Pac-Islander tends to earn Masters early in␣
↪their age.
# Average age of people in specific race who are in either Prof-specialty or␣
↪Exec-managerial
# occupation and completed Masters degree  excluding race categorized as other.
# Asian-Pac-Islander tends to earn Masters early in their age.


from bson.code import Code
mapFunction = Code("""function() {
                                    emit(this.race, this.age);}""")

reduceFunction = Code("""function(key, values) {
                                                sum = Array.avg(values);
                                                return Math.round(sum, 2)}""")

# store results in a cursor, a new collection name race_education will be␣
↪reated in mongodb
cur = collection.map_reduce( mapFunction, reduceFunction,
                             "race_education" , query={"$and": [ {
              "$and": [{"occupation": {"$in": [ "Prof-specialty",␣
↪"Exec-managerial"]}},
                      {"education": {"$eq": "Masters"}}]}, {"race": {"$ne":␣
↪"Other"}}]})

# for loop to iterate through the documents in the cursor
for doc in cur.find(sort=[("value", pymongo.DESCENDING)]).limit(5):
    pprint.pprint (doc)
```

```
{'_id': 'Amer-Indian-Eskimo', 'value': 47.0}
{'_id': 'White', 'value': 43.0}
```

```
{'_id': 'Black', 'value': 42.0}
{'_id': 'Asian-Pac-Islander', 'value': 37.0}
```

Note: For other queries please refer the presentation.

## 1.1 Data Wrangling

### 1.1.1 Converting MongoDB collection to pandas dataframe

[188]:
```
# to convert MongoDB collection into Pandas dataframe using'json_normalize' in␣
↪Pandas

# import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.io.json import json_normalize

censuspd = collection
df = json_normalize(list(censuspd.find()))
```

### 1.1.2 Initial exploration

[189]:
```
# to check data frame column types

df.dtypes
```

[189]:
```
_id                object
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
native_country     object
income             object
dtype: object
```

[190]:
```
# to display a few rows from the dataframe
df.head(5)
```

```python
# to display dataframe dimensions
df.shape
```

[190]:
```
                          _id  age workclass  fnlwgt     education  \
0  5e4a23cd61c3cdf1528a4508   90         ?   77053       HS-grad
1  5e4a23cd61c3cdf1528a4509   82   Private  132870       HS-grad
2  5e4a23cd61c3cdf1528a450a   66         ?  186061  Some-college
3  5e4a23cd61c3cdf1528a450b   54   Private  140359       7th-8th
4  5e4a23cd61c3cdf1528a450c   41   Private  264663  Some-college

   education_num marital_status         occupation   relationship   race  \
0              9        Widowed                  ?  Not-in-family  White
1              9        Widowed    Exec-managerial  Not-in-family  White
2             10        Widowed                  ?      Unmarried  Black
3              4       Divorced  Machine-op-inspct      Unmarried  White
4             10      Separated     Prof-specialty      Own-child  White

      sex  capital_gain  capital_loss  hours_per_week native_country income
0  Female             0          4356              40  United-States  <=50K
1  Female             0          4356              18  United-States  <=50K
2  Female             0          4356              40  United-States  <=50K
3  Female             0          3900              40  United-States  <=50K
4  Female             0          3900              40  United-States  <=50K
```

[190]: (32561, 16)

### 1.1.3 Feature Engineering

**Remove unnecessary columns**

- Education and education_num: These variables represent the same data with education_num as ordinal representation.
- fnlwgt
- relationship
- _id: id generated by MongoDB

[191]:
```python
# drop education_num, fnlwgt, relationship, _id columns
df.drop(labels=["education_num", "fnlwgt", "relationship", "_id"], axis = 1,␣
↪inplace = True)
# to check the dataframe aster the update
df.head(5)
```

[191]:
```
   age workclass     education marital_status         occupation   race  \
0   90         ?       HS-grad        Widowed                  ?  White
1   82   Private       HS-grad        Widowed    Exec-managerial  White
2   66         ?  Some-college        Widowed                  ?  Black
3   54   Private       7th-8th       Divorced  Machine-op-inspct  White
4   41   Private  Some-college      Separated     Prof-specialty  White
```

```
      sex  capital_gain  capital_loss  hours_per_week native_country income
0  Female             0          4356              40  United-States  <=50K
1  Female             0          4356              18  United-States  <=50K
2  Female             0          4356              40  United-States  <=50K
3  Female             0          3900              40  United-States  <=50K
4  Female             0          3900              40  United-States  <=50K
```

**capital_gain and capital_loss** Next, the capital_gain and capital_loss columns can be combined into a single column capital. Further, capital_gain and capital_loss columns can be removed to aid the analysis, using the following code:

[192]:
```
# a positive value represents gain and a negative value represents loss
df["capital"] = df["capital_gain"] - df["capital_loss"]

# drop capital_gain & capital_loss
df.drop(labels=["capital_gain", "capital_loss"], axis = 1, inplace = True)
df.head(5)
```

[192]:
```
   age workclass     education marital_status         occupation   race  \
0   90         ?       HS-grad        Widowed                  ?  White
1   82   Private       HS-grad        Widowed    Exec-managerial  White
2   66         ?  Some-college        Widowed                  ?  Black
3   54   Private       7th-8th       Divorced  Machine-op-inspct  White
4   41   Private  Some-college      Separated     Prof-specialty  White

      sex  hours_per_week native_country income  capital
0  Female              40  United-States  <=50K    -4356
1  Female              18  United-States  <=50K    -4356
2  Female              40  United-States  <=50K    -4356
3  Female              40  United-States  <=50K    -3900
4  Female              40  United-States  <=50K    -3900
```

**Combine Native Country column catagories** There are too many categories in native_country column, it can be reduced to their respective regions and key countries can be kept. The countries are categorized among their respective regions and leaving key countries such as the US to see if native to the countries make any difference to the income classification.

[193]:
```
# to combine countries in limited continents, and major countries

df["native_country"] = df["native_country"].
↪replace(["Dominican-Republic","Guatemala","Haiti","Honduras",
"Jamaica","Mexico","Nicaragua", "Outlying-US(Guam-USVI-etc)",
"Puerto-Rico","Trinadad&Tobago","Cuba"], 'LatinAmerica')
```

```
df["native_country"] = df["native_country"].
 ↪replace(["Peru","Ecuador","El-Salvador","Columbia"], 'SouthAmerica')

df["native_country"] = df["native_country"].
 ↪replace(["France","Germany","Greece","Holand-Netherlands",
"Hungary","Italy","Poland", "Portugal","Puerto-Rico",
"South","Ireland","Yugoslavia"], 'Europe')

df["native_country"] = df["native_country"].
 ↪replace(["China","Hong","India","Japan","Iran"], 'Asia')

df["native_country"] = df["native_country"].
 ↪replace(["Vietnam","Cambodia","Thailand","Laos","Philippines","Taiwan"],␣
 ↪'SE_Asia')

df["native_country"] = df["native_country"].replace(["England","Scotland"],␣
 ↪'UK')

df["native_country"] = df["native_country"].replace(["United-States"], 'US')

df.head(5)
```

[193]:

```
   age workclass     education marital_status         occupation   race  \
0   90         ?       HS-grad        Widowed                  ?  White
1   82   Private       HS-grad        Widowed    Exec-managerial  White
2   66         ?  Some-college        Widowed                  ?  Black
3   54   Private       7th-8th       Divorced  Machine-op-inspct  White
4   41   Private  Some-college      Separated     Prof-specialty  White

      sex  hours_per_week native_country income  capital
0  Female              40             US  <=50K    -4356
1  Female              18             US  <=50K    -4356
2  Female              40             US  <=50K    -4356
3  Female              40             US  <=50K    -3900
4  Female              40             US  <=50K    -3900
```

**Combine Education column catagories** Similarly, categories in education column can be combined into a fewer columns to make the modeling more efficient.

[194]:

```
# to combine education into limited categories
df["education"] = df["education"].replace(['10th','11th', '12th', '1st-4th',␣
 ↪'5th-6th', '7th-8th', '9th', 'Preschool'], 'No-college')
df["education"] = df["education"].replace(['Assoc-acdm','Assoc-voc'],␣
 ↪'Associates')
df.head(5)
```

[194]:
```
   age workclass     education marital_status         occupation   race  \
0   90         ?       HS-grad        Widowed                  ?  White
1   82   Private       HS-grad        Widowed    Exec-managerial  White
2   66         ?  Some-college        Widowed                  ?  Black
3   54   Private    No-college       Divorced  Machine-op-inspct  White
4   41   Private  Some-college      Separated     Prof-specialty  White

      sex  hours_per_week native_country income  capital
0  Female              40             US  <=50K    -4356
1  Female              18             US  <=50K    -4356
2  Female              40             US  <=50K    -4356
3  Female              40             US  <=50K    -3900
4  Female              40             US  <=50K    -3900
```

**Combine Workclass column categories** Next, categories in workclass column can be combined into fewer categories as follows:

[195]:
```
df["workclass"] = df["workclass"].replace(['Without-pay','Never-worked'],␣
↪'Not-Working')
df["workclass"] = df["workclass"].replace(['Self-emp-not-inc','Self-emp-inc'],␣
↪'Self-Employed')
df.head(5)
```

[195]:
```
   age workclass     education marital_status         occupation   race  \
0   90         ?       HS-grad        Widowed                  ?  White
1   82   Private       HS-grad        Widowed    Exec-managerial  White
2   66         ?  Some-college        Widowed                  ?  Black
3   54   Private    No-college       Divorced  Machine-op-inspct  White
4   41   Private  Some-college      Separated     Prof-specialty  White

      sex  hours_per_week native_country income  capital
0  Female              40             US  <=50K    -4356
1  Female              18             US  <=50K    -4356
2  Female              40             US  <=50K    -4356
3  Female              40             US  <=50K    -3900
4  Female              40             US  <=50K    -3900
```

**Combine Marital Status column catagories** Next, collalte marital_status column values into 3 categories - Married, Not-married, Never-married using the following code:

[196]:
```
df["marital_status"] = df["marital_status"].
↪replace(['Never-married','Divorced','Separated','Widowed'], 'Single')
df["marital_status"] = df["marital_status"].
↪replace(['Married-civ-spouse','Married-spouse-absent','Married-AF-spouse'],␣
↪'Married')
df.head(5)
```

```
[196]:    age  workclass     education marital_status         occupation   race  \
       0   90          ?       HS-grad         Single                  ?  White
       1   82    Private       HS-grad         Single    Exec-managerial  White
       2   66          ?  Some-college         Single                  ?  Black
       3   54    Private    No-college         Single  Machine-op-inspct  White
       4   41    Private  Some-college         Single     Prof-specialty  White

             sex  hours_per_week native_country income  capital
       0  Female              40             US  <=50K    -4356
       1  Female              18             US  <=50K    -4356
       2  Female              40             US  <=50K    -4356
       3  Female              40             US  <=50K    -3900
       4  Female              40             US  <=50K    -3900
```

#### 1.1.4 Remove Duplicate Records

```
[197]: # drop the duplicate rows
df = df.drop_duplicates(keep = 'first')

df.shape
```

```
[197]: (27057, 11)
```

#### 1.1.5 Impute missing values

To prepare the dataset for analysis, getting rid if missing values in an important step. The easiest method is to replace the missing values with the mean for numerical variables; however, it makes more sense to remove records with missing values for categorical attribtes.

```
[198]: # to find the columns with ? value

print ("column    :   ? count")
print("----------------------")
for i in df.columns:
    t = df[i].value_counts()
    index = list(t.index)
    for j in index:
        if j == '?':
            print (i," : ",t['?'])
            break
```

```
column    :   ? count
---------------------
workclass  :  1540
occupation  :  1547
native_country  :  579
```

[199]:
```python
# update '?' to NaN
df['workclass'].replace('?', np.NaN, inplace = True)
df['occupation'].replace('?', np.NaN, inplace = True)
df['native_country'].replace('?', np.NaN, inplace = True)

# to check if all '?' updated to NaN
df.isnull().sum()
```

[199]:
```
age                  0
workclass         1540
education            0
marital_status       0
occupation        1547
race                 0
sex                  0
hours_per_week       0
native_country     579
income               0
capital              0
dtype: int64
```

[200]:
```python
# to remove all rows with null values
df=df.dropna()
# to check the shape after the removal
df.shape
```

[200]:
```
(24958, 11)
```

## 1.2 Exploratory Data Analysis & Visualization

[201]:
```python
df.describe()
```

[201]:

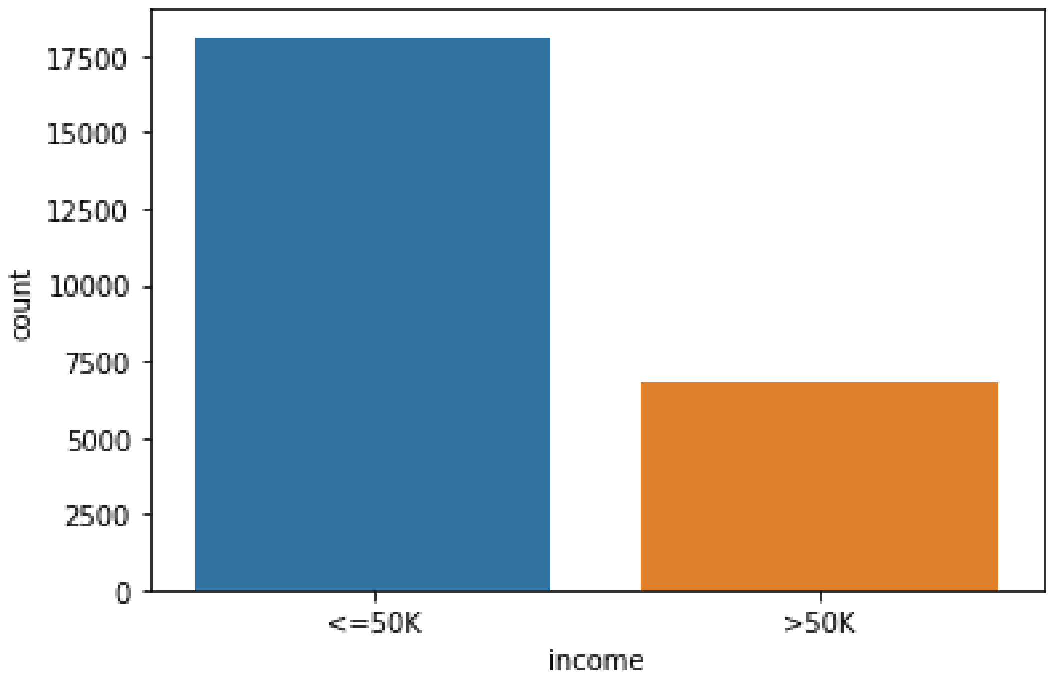
| | age | hours_per_week | capital |
|---|---|---|---|
| count | 24958.000000 | 24958.000000 | 24958.000000 |
| mean | 39.531653 | 41.363611 | 1203.482931 |
| std | 13.194469 | 12.662223 | 8124.852635 |
| min | 17.000000 | 1.000000 | -4356.000000 |
| 25% | 29.000000 | 40.000000 | 0.000000 |
| 50% | 38.000000 | 40.000000 | 0.000000 |
| 75% | 48.000000 | 48.000000 | 0.000000 |
| max | 90.000000 | 99.000000 | 99999.000000 |

[202]:
```python
df['income'].value_counts()

# Count of >50K & <=50K
sns.countplot(df['income'],label="Count")
```

[202]:
```
<=50K    18126
>50K      6832
Name: income, dtype: int64
```

[202]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x13b39818b88>
```




**Visualizations:** Exploratory data analysis visualizations are created through Tableau and and can be found on the Tableau Public server.

https://public.tableau.com/profile/ravi7131#!/vizhome/Adult_Census_Salary/AdultCensusSalary

### 1.3 Modeling

[203]:
```python
# import section

from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from scipy import stats
import pylab as pl
from sklearn.ensemble import RandomForestRegressor
from sklearn.cluster import KMeans
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPRegressor
```

### 1.3.1 Encoding: One-Hot Encode Factors

Now, let's do some data processing to make the data suitable (and often essential) for modeling classifier models.One-hot encoding is a process to convert to multiple binarized vectors from categorical vectors. Each 1s and 0s binary vector indicates the presence of the original vector class or levels. Categorical variables are translated into a type in this method that could help make algorithms more efficient; however, the number of columns is expanded.

[204]:
```python
# to factoring variables to exclude the unwanted levels

from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
#item_encod = list(label_encoder.fit_transform())
df = pd.get_dummies(df)
df.head(5)
```

[204]:
```
   age  hours_per_week  capital  workclass_Federal-gov  workclass_Local-gov  \
1   82              18    -4356                      0                    0
3   54              40    -3900                      0                    0
4   41              40    -3900                      0                    0
5   34              45    -3770                      0                    0
6   38              40    -3770                      0                    0

   workclass_Not-Working  workclass_Private  workclass_Self-Employed  \
1                      0                  1                        0
3                      0                  1                        0
4                      0                  1                        0
5                      0                  1                        0
6                      0                  1                        0

   workclass_State-gov  education_Associates  …  native_country_Asia  \
1                    0                     0  …                    0
3                    0                     0  …                    0
4                    0                     0  …                    0
5                    0                     0  …                    0
6                    0                     0  …                    0

   native_country_Canada  native_country_Europe  native_country_LatinAmerica  \
1                      0                      0                            0
3                      0                      0                            0
4                      0                      0                            0
5                      0                      0                            0
6                      0                      0                            0

   native_country_SE_Asia  native_country_SouthAmerica  native_country_UK  \
1                       0                            0                  0
3                       0                            0                  0
4                       0                            0                  0
```

```
5                      0                            0                  0
6                      0                            0                  0

   native_country_US  income_<=50K  income_>50K
1                  1             1            0
3                  1             1            0
4                  1             1            0
5                  1             1            0
6                  1             1            0

[5 rows x 50 columns]
```

[205]:

```
# the target label can be combined into a single feature. value 0 represents␣
↪income less than or equal to 50k
# and a value of 1 represents income greater than 50k

df["income"] = df["income_>50K"]
# drop income_>50K & income_<=50K
df.drop(labels=["income_<=50K", "income_>50K"], axis = 1, inplace = True)
df.head(5)
```

[205]:

```
   age  hours_per_week  capital  workclass_Federal-gov  workclass_Local-gov  \
1   82              18    -4356                      0                    0
3   54              40    -3900                      0                    0
4   41              40    -3900                      0                    0
5   34              45    -3770                      0                    0
6   38              40    -3770                      0                    0

   workclass_Not-Working  workclass_Private  workclass_Self-Employed  \
1                      0                  1                        0
3                      0                  1                        0
4                      0                  1                        0
5                      0                  1                        0
6                      0                  1                        0

   workclass_State-gov  education_Associates  …  sex_Male  \
1                    0                     0  …         0
3                    0                     0  …         0
4                    0                     0  …         0
5                    0                     0  …         0
6                    0                     0  …         1

   native_country_Asia  native_country_Canada  native_country_Europe  \
1                    0                      0                      0
3                    0                      0                      0
4                    0                      0                      0
5                    0                      0                      0
```

```
6                    0                    0                    0

   native_country_LatinAmerica  native_country_SE_Asia  \
1                            0                       0
3                            0                       0
4                            0                       0
5                            0                       0
6                            0                       0

   native_country_SouthAmerica  native_country_UK  native_country_US  income
1                            0                  0                  1       0
3                            0                  0                  1       0
4                            0                  0                  1       0
5                            0                  0                  1       0
6                            0                  0                  1       0

[5 rows x 49 columns]
```

### 1.3.2 Labels Dataset

[206]:
```
#extract 'income' column of dataset to labels datasets
x = df.drop(['income'], axis=1)
# then remove income label from the train and test dataset
y = df['income']

# to check the shape of the datasets
x.shape
y.shape
```

[206]: (24958, 48)

[206]: (24958,)

### 1.3.3 Spliting dataset: Training and Validation Sets

[207]:
```
# split the dataset into 70 / 30 ratio with random split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3,␣
↪random_state = 0)
```

### 1.3.4 Feature Scaling

Next, all the features will be scaled-up. It's a technique that scales all the characteristics that speeds up the models' training time as all features are on the same scale. The code used in the scaling of the function follows:

[208]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns = x.columns)

x_test = pd.DataFrame(scaler.transform(x_test), columns = x.columns)

x_train.shape
x_train.head(10)

x_test.shape
x_test.head(10)
```

[208]: (17470, 48)

[208]:
```
        age  hours_per_week   capital  workclass_Federal-gov  \
0 -0.264510       -0.107317 -0.147556              -0.195638
1  0.341234       -0.503319 -0.147556              -0.195638
2 -0.945973       -0.107317 -0.147556               5.111490
3 -0.567383       -0.107317 -0.147556              -0.195638
4 -0.643101       -0.107317 -0.147556              -0.195638
5 -1.627436       -2.166528 -0.071118              -0.195638
6 -0.567383       -0.265718 -0.147556              -0.195638
7 -0.945973       -0.899321 -0.147556              -0.195638
8 -1.248845       -0.107317 -0.147556              -0.195638
9  0.795542       -0.344918 -0.147556              -0.195638

   workclass_Local-gov  workclass_Not-Working  workclass_Private  \
0            -0.295503              -0.021404           0.657689
1            -0.295503              -0.021404           0.657689
2            -0.295503              -0.021404          -1.520476
3            -0.295503              -0.021404           0.657689
4            -0.295503              -0.021404          -1.520476
5            -0.295503              -0.021404           0.657689
6            -0.295503              -0.021404           0.657689
7            -0.295503              -0.021404          -1.520476
8            -0.295503              -0.021404           0.657689
9            -0.295503              -0.021404          -1.520476

   workclass_Self-Employed  workclass_State-gov  education_Associates  …  \
0                -0.394819            -0.228100              3.272478  …
1                -0.394819            -0.228100             -0.305579  …
2                -0.394819            -0.228100              3.272478  …
3                -0.394819            -0.228100             -0.305579  …
4                -0.394819             4.384051             -0.305579  …
5                -0.394819            -0.228100             -0.305579  …
6                -0.394819            -0.228100             -0.305579  …
7                -0.394819             4.384051             -0.305579  …
8                -0.394819            -0.228100             -0.305579  …
```

```
9              -0.394819             4.384051             -0.305579  ...

   sex_Female  sex_Male  native_country_Asia  native_country_Canada  \
0   -0.688486  0.688486            -0.104299              -0.065663
1    1.452463 -1.452463            -0.104299              -0.065663
2   -0.688486  0.688486            -0.104299              -0.065663
3   -0.688486  0.688486            -0.104299              -0.065663
4   -0.688486  0.688486            -0.104299              -0.065663
5   -0.688486  0.688486            -0.104299              -0.065663
6   -0.688486  0.688486            -0.104299              -0.065663
7    1.452463 -1.452463            -0.104299              -0.065663
8    1.452463 -1.452463            -0.104299              -0.065663
9    1.452463 -1.452463            -0.104299              -0.065663

   native_country_Europe  native_country_LatinAmerica  native_country_SE_Asia  \
0              -0.137032                    -0.211793               -0.121707
1              -0.137032                    -0.211793               -0.121707
2              -0.137032                    -0.211793               -0.121707
3              -0.137032                    -0.211793               -0.121707
4              -0.137032                    -0.211793               -0.121707
5              -0.137032                    -0.211793               -0.121707
6              -0.137032                    -0.211793               -0.121707
7              -0.137032                    -0.211793               -0.121707
8              -0.137032                    -0.211793               -0.121707
9              -0.137032                    -0.211793               -0.121707

   native_country_SouthAmerica  native_country_UK  native_country_US
0                    -0.093062          -0.063427           0.339972
1                    -0.093062          -0.063427           0.339972
2                    -0.093062          -0.063427           0.339972
3                    -0.093062          -0.063427           0.339972
4                    -0.093062          -0.063427           0.339972
5                    -0.093062          -0.063427           0.339972
6                    -0.093062          -0.063427           0.339972
7                    -0.093062          -0.063427           0.339972
8                    -0.093062          -0.063427           0.339972
9                    -0.093062          -0.063427           0.339972

[10 rows x 48 columns]
```

[208]:
```
(7488, 48)
```

[208]:
```
        age  hours_per_week   capital  workclass_Federal-gov  \
0  0.038362       -0.503319 -0.147556              -0.195638
1 -1.324563       -0.899321 -0.147556              -0.195638
2 -1.097409       -0.107317  0.280318              -0.195638
3 -0.870255       -0.107317  1.206198              -0.195638
```

```
4 -0.718819        0.288685 -0.147556             -0.195638
5 -1.475999       -0.503319 -0.147556             -0.195638
6 -1.627436        1.080689 -0.147556             -0.195638
7 -0.491665        0.526286 -0.147556             -0.195638
8  0.114080       -0.661720 -0.147556             -0.195638
9  0.341234        0.288685  0.416851             -0.195638

   workclass_Local-gov  workclass_Not-Working  workclass_Private  \
0            -0.295503              -0.021404           0.657689
1            -0.295503              -0.021404           0.657689
2            -0.295503              -0.021404           0.657689
3            -0.295503              -0.021404           0.657689
4            -0.295503              -0.021404          -1.520476
5            -0.295503              -0.021404           0.657689
6            -0.295503              -0.021404           0.657689
7            -0.295503              -0.021404           0.657689
8            -0.295503              -0.021404           0.657689
9            -0.295503              -0.021404           0.657689

   workclass_Self-Employed  workclass_State-gov  education_Associates  …  \
0                -0.394819              -0.2281             -0.305579  …
1                -0.394819              -0.2281             -0.305579  …
2                -0.394819              -0.2281             -0.305579  …
3                -0.394819              -0.2281             -0.305579  …
4                 2.532807              -0.2281             -0.305579  …
5                -0.394819              -0.2281             -0.305579  …
6                -0.394819              -0.2281             -0.305579  …
7                -0.394819              -0.2281             -0.305579  …
8                -0.394819              -0.2281             -0.305579  …
9                -0.394819              -0.2281              3.272478  …

   sex_Female  sex_Male  native_country_Asia  native_country_Canada  \
0    1.452463 -1.452463            -0.104299              -0.065663
1    1.452463 -1.452463            -0.104299              -0.065663
2    1.452463 -1.452463            -0.104299              -0.065663
3    1.452463 -1.452463            -0.104299              -0.065663
4   -0.688486  0.688486            -0.104299              -0.065663
5   -0.688486  0.688486            -0.104299              -0.065663
6   -0.688486  0.688486            -0.104299              -0.065663
7   -0.688486  0.688486            -0.104299              -0.065663
8   -0.688486  0.688486            -0.104299              -0.065663
9   -0.688486  0.688486            -0.104299              -0.065663

   native_country_Europe  native_country_LatinAmerica  native_country_SE_Asia  \
0              -0.137032                    -0.211793               -0.121707
1              -0.137032                     4.721582               -0.121707
2              -0.137032                    -0.211793               -0.121707
```

```
3              -0.137032                    -0.211793                -0.121707
4              -0.137032                    -0.211793                -0.121707
5              -0.137032                    -0.211793                -0.121707
6              -0.137032                    -0.211793                -0.121707
7              -0.137032                    -0.211793                -0.121707
8              -0.137032                    -0.211793                -0.121707
9              -0.137032                    -0.211793                -0.121707

   native_country_SouthAmerica  native_country_UK  native_country_US
0                    -0.093062          -0.063427           0.339972
1                    -0.093062          -0.063427          -2.941417
2                    -0.093062          -0.063427           0.339972
3                    -0.093062          -0.063427           0.339972
4                    -0.093062          -0.063427           0.339972
5                    -0.093062          -0.063427           0.339972
6                    -0.093062          -0.063427           0.339972
7                    -0.093062          -0.063427           0.339972
8                    -0.093062          -0.063427           0.339972
9                    -0.093062          -0.063427           0.339972

[10 rows x 48 columns]
```

### 1.3.5 Logistic Regression Model

[209]:
```python
# import block
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# to create logistic regression model
log_model = LogisticRegression()
log_model.fit(x_train, y_train)
y_pred = log_model.predict(x_test)

print('Logistic Regression accuracy score with all the features: {0:0.4f}'.
 ↪format(accuracy_score(y_test, y_pred)))
```

[209]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
Logistic Regression accuracy score with all the features: 0.8224
```

[210]:
```python
acc_log = str(round(metrics.accuracy_score(np.round(y_test),np.round(y_pred)),
 ↪2) * 100)+"%"
mse_log = round(metrics.mean_squared_error(y_test,y_pred), 4)
```

```
r2s_log = round(metrics.r2_score(y_test,y_pred), 4)


res_df = pd.DataFrame({
        "Model": ['Logistic Regression'],
        'Accuracy': [acc_log],
        'Mean Squared Error' : [mse_log],
        'R2 Score': [r2s_log]
})

res_df
```

[210]:

| | Model | Accuracy | Mean Squared Error | R2 Score |
|---|---|---|---|---|
| 0 | Logistic Regression | 82.0% | 0.1776 | 0.117 |

### 1.3.6 Random Forest Model

[211]:

```
rf_model = RandomForestRegressor(max_features= 'log2'␣
↪,n_estimators=6,criterion='mse',min_samples_leaf=2,
                                  oob_score=True, n_jobs=-1, random_state=0)
rf_model.fit(x_train, y_train)
rdpreds = rf_model.predict(x_test)
print(rdpreds)
```

[211]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='log2', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=2,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=6, n_jobs=-1, oob_score=True, random_state=0,
                      verbose=0, warm_start=False)
```

```
[0.07477969 0.00438596 0.19837059 … 0.5112781  0.04987495 0.57562418]
```

[212]:

```
acc_rf = str(round(metrics.accuracy_score(np.round(y_test),np.round(rdpreds)),␣
↪2) * 100)+"%"
mse_rf = round(metrics.mean_squared_error(y_test, rdpreds), 4)
r2s_rf = round(metrics.r2_score(y_test, rdpreds), 4)

res_rf = pd.DataFrame({
        'Model': ["Random Forest"],
        'Accuracy': [acc_rf],
        'Mean Squared Error' : [mse_rf],
        'R2 Score': [r2s_rf]
})

res_df = res_df.append(res_rf)
```

```
res_df
```

[212]:

| | Model | Accuracy | Mean Squared Error | R2 Score |
|---|---|---|---|---|
| 0 | Logistic Regression | 82.0% | 0.1776 | 0.1170 |
| 0 | Random Forest | 83.0% | 0.1169 | 0.4191 |

### 1.3.7 K_Nearest Neighbors

[214]:
```
knn_model = KNeighborsRegressor(n_neighbors = 12, algorithm = 'ball_tree',␣
↪leaf_size=1000, metric='manhattan',p=3,n_jobs=-1)
knn_model.fit(x_train, y_train)
knn_preds = knn_model.predict(x_test)
print(knn_preds)
```

[214]:
```
KNeighborsRegressor(algorithm='ball_tree', leaf_size=1000, metric='manhattan',
                    metric_params=None, n_jobs=-1, n_neighbors=12, p=3,
                    weights='uniform')
```

```
[0.16666667 0.         0.08333333 … 0.33333333 0.08333333 0.66666667]
```

[173]:
```
acc_knn = str(round(metrics.accuracy_score(np.round(y_test),np.
↪round(knn_preds)), 2) * 100)+"%"
mse_knn = round(metrics.mean_squared_error(y_test, knn_preds), 4)
r2s_knn = round(metrics.r2_score(y_test, knn_preds), 4)

res_knn =  pd.DataFrame({
            'Model': ["K-Nearest Neighbors"],
            'Accuracy': [acc_knn],
            'Mean Squared Error' : [mse_knn],
            'R2 Score': [r2s_knn]
})

res_df =res_df.append(res_knn)

res_df
```

[173]:

| | Model | Accuracy | Mean Squared Error | R2 Score |
|---|---|---|---|---|
| 0 | Logistic Regression | 82.0% | 0.1776 | 0.1170 |
| 0 | Random Forest | 83.0% | 0.1169 | 0.4191 |
| 0 | K-Nearest Neighbors | 81.0% | 0.1322 | 0.3425 |

## 1.4 Results

The results of the accuracy of various models are listed below. The Random Forest Model achieved the highest accuracy and the ultimately proposed model of all models explored in this project.

In this project, the popluar analysis and modeling approaches are used to keep it limited to the scope of the project. Nonetheless, more advanced modeling methods such as NNET, Deep Neural

Network, etc. as well as modeling with features based on their importance could be used as a potential extension of this project to further improve the performance. In addition, other significant comparison quality features including Sensitivity, Specificity, Prevalence, F1 Score, AUC, ROC curve can be explored further.