# income_inequality

September 14, 2021

## 1 Predicting Income Inequality from U.S. Census Data

In this project, we will be utilizing data from UCI's Machine Learning Repository in order to predict income from U.S. census data.

We'll be using a random forest to filter through the values derived from our trees, and obtain our optimal classifier.

#### 1.0.1 Imports

We're going to be using pandas and sklearn for this functionality.

[20]:
```
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
%matplotlib inline
```

### 1.1 Investigating The Data

First we will read in the data and take a look at the initial values.

[21]:
```
# reading in the income data to a df
income_data = pd.read_csv('income.csv', delimiter = ', ', header=0)

# printing the first
print(f'First income data point:\n{income_data.iloc[0]}')

# grabbing only the 'income' column for assigning our labels
labels = income_data[['income']]
```

```
First income data point:
age                     39
workclass        State-gov
fnlwgt               77516
education        Bachelors
```

```
education-num                  13
marital-status      Never-married
occupation           Adm-clerical
relationship        Not-in-family
race                        White
sex                          Male
capital-gain                 2174
capital-loss                    0
hours-per-week                 40
native-country      United-States
income                      <=50K
Name: 0, dtype: object
```

### 1.1.1 Data Cleaning

In order for us to use our machine, we need to transform the data slightly. We'll be changing the `sex`, and `native-country` columns to binary values.

[22]:
```
# changing the 'sex' and 'country' columns to be binary values for ML
income_data['sex-int'] = income_data['sex'].apply(lambda x: 0 if x == 'Male'␣
 ↪else 1)
income_data['country-int'] = income_data['native-country'].apply(lambda x: 0 if␣
 ↪x == 'United-States' else 1)

# creating the 'data' section for our machine
data = income_data[['age', 'capital-gain', 'capital-loss', 'hours-per-week',␣
 ↪'sex-int', 'country-int']]
```

## 1.2 Building The Model

Now we can split the data into training and testing sets, default split is 75% training and 25% testing. Then we can create our random forest and test it's performance on the set.

[23]:
```
train_data, test_data, train_labels, test_labels = train_test_split(data,␣
 ↪labels, random_state=1)

# creating the random forest, default is 100 trees
forest = RandomForestClassifier(random_state=1)
forest.fit(train_data, train_labels)

# printing the score of our forest
print(forest.score(test_data, test_labels))
```

```
0.8225033779633951
```

This score is pretty good, but let's see if we can't get a better one!

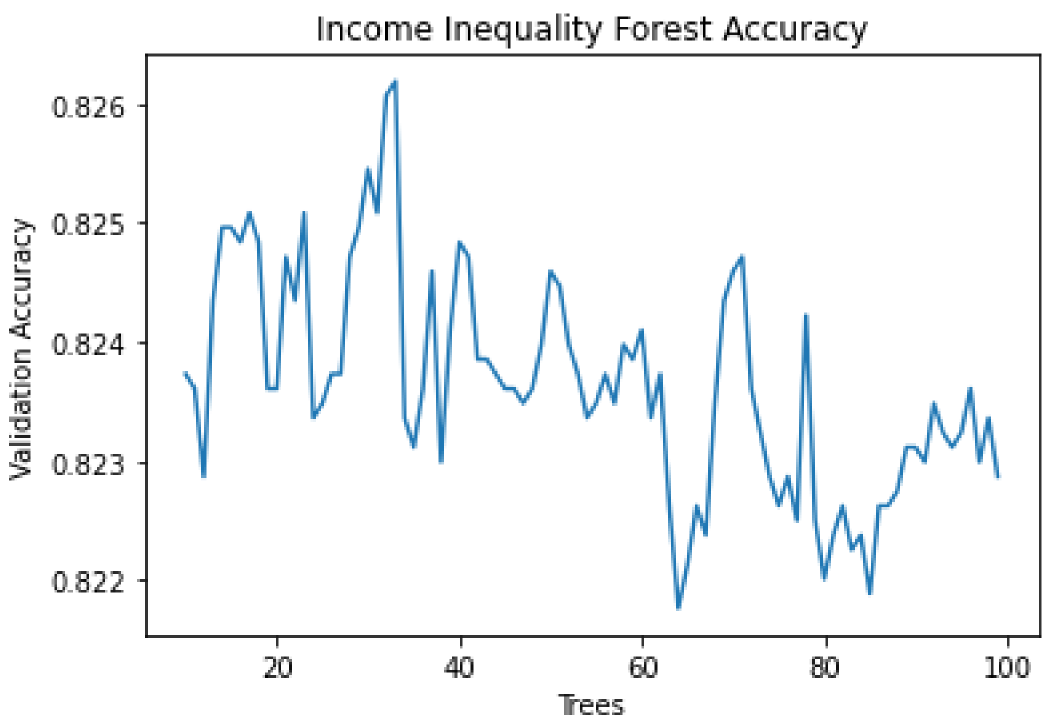
## 1.3 Improving The Model

We change change the number of trees we name to determine the optimal number of trees.

[28]:
```python
# creating a dict for our forest scores
forest_scores = {}
for i in range(10, 100):
    forest = RandomForestClassifier(random_state=1, n_estimators=i)
    forest.fit(train_data, train_labels)
    forest_scores[i] = forest.score(test_data, test_labels)
```

[29]:
```python
plt.plot(*zip(*forest_scores.items()))
plt.xlabel('Trees')
plt.ylabel('Validation Accuracy')
plt.title('Income Inequality Forest Accuracy')
plt.show()

max_score = max(forest_scores.values())
print(f'The best score ({max_score}) comes from a forest with␣
↪{max(forest_scores, key=forest_scores.get)} trees!')
```




```
The best score (0.8261884289399337) comes from a forest with 33 trees!
```

In conclusion, we can predict whether someone will make over $50k based solely off census data with an accuracy of 83%!

**Data Sources** Data is derived from the UCI's Machine Learning Repository.