JakeDineen_Homework1_CensusData

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Homework 1

Structured Data Processing Task
In addition to the program that you write, you should write a small report. In it you should provide:

- Data and its source
- Description of your data exploration and data cleaning steps
- At least two clearly stated comparison questions with the unit of analysis, the comparison values, and how they are computed
- Brief description of the program
- Description of the output files

For this assignment I'll be looking at some US Census data via the following repository:
ml/machine-learning-databases/adult/adult.data

I've chosen to write this all in 'Markdown' type format via Jupyter Notebooks to keep my code and responses together, and to allow for easier to follow analysis.

There are 48842 instances x 14 attributes available, including some demographic and socioeconomic responses. The data was collected from the 1994 Census Database. Overall, the main goal of the dataset is to predict whether or not a person makes >=50k based on the various regressors, but because this task is more exploratory, I'm not sure if I will use a modeling technique to derive information - Although I may, because I can show feature ranking of gradient boosted trees and see which of these variables is the most influential on yearly income.

A variable dictionary, as defined by the site:

- age: continuous.
- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- fnlwgt: continuous.
- education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- education-num: continuous.
- marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

- occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- sex: Female, Male.
- capital-gain: continuous.
- capital-loss: continuous.
- hours-per-week: continuous.
- native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

Some of these may be superflous for the task at hand, and others could likely be binned down to reduce variance, so I might toy around with some feature engineering for EDA/inference.

Reading in the data I am reading the data in from a csv html link. Pandas seems like the easiest way to process this data and put it into a dataframe, which is what I am looking to do.

```
In [62]: import csv
         import numpy as np
         import pandas as pd
         import sklearn
         import os

         #Simple try catch for reading in the data.
         try:
             #Reading in the data
             data = 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data

             #Read in the data into a pandas df with column names (col names not included via
             data = pd.read_csv(data, names = ['Age', 'Workclass', 'finalweight', 'education',
                                         'occupation', 'relationship', 'race', 'sex', 'capitalga
                                         'hoursperweek', 'native_country', 'Class'])

         except:
             print('Something went wrong')

         #Print data head for inspection
         data.head(n=5)
```

```
Out[62]:    Age         Workclass  finalweight   education  education_num  \
         0   39         State-gov        77516   Bachelors             13
         1   50  Self-emp-not-inc        83311   Bachelors             13
         2   38           Private       215646     HS-grad              9
```

```
3   53             Private       234721         11th              7
4   28             Private       338409    Bachelors             13

        marital_status          occupation    relationship    race      sex  \
0        Never-married        Adm-clerical   Not-in-family   White     Male
1   Married-civ-spouse     Exec-managerial         Husband   White     Male
2             Divorced   Handlers-cleaners   Not-in-family   White     Male
3   Married-civ-spouse   Handlers-cleaners         Husband   Black     Male
4   Married-civ-spouse      Prof-specialty            Wife   Black   Female

   capitalgain  capitalloss  hoursperweek  native_country   Class
0         2174            0            40   United-States   <=50K
1            0            0            13   United-States   <=50K
2            0            0            40   United-States   <=50K
3            0            0            40   United-States   <=50K
4            0            0            40            Cuba   <=50K
```

In [63]:
```
print('Read in {} rows & {} columns'.format(data.shape[0], data.shape[1]))
```

```
Read in 32561 rows & 15 columns
```

Cleaning the data. This data is already highly structured, although there are some things that I'd like to do: - remove the finalweight var. This seems more sequential than anything else. I've worked with this data in the past and still struggle to understand exactly how that weighting is formulated. - remove education_num as a var. This is redundant as we already have an education variable, and it's slightly more intuitive than a continous count of grade. It will be factorized when modeling anyways, so it makes more sense to have it grouped into more specific bins. - Look at a histogram of country to see if there's any instances that we'd be better off removing - eg. if Jamaica only has a few observations, it would be tough to account for the variance there. - Find out about missing values and deal with them through dropping or imputing.

In [64]:
```
#Remove Specified Columns
colstodrop = ['finalweight', 'education_num']
data.drop(columns =colstodrop, inplace = True) #inplace = true to replace without res
for i in colstodrop:
    print('Dropping',i)
data.head(n=3)
```

```
Dropping finalweight
Dropping education_num
```

Out[64]:
```
   Age          Workclass   education        marital_status  \
0   39          State-gov   Bachelors         Never-married
1   50   Self-emp-not-inc   Bachelors    Married-civ-spouse
2   38            Private     HS-grad              Divorced
```

```
             occupation    relationship    race    sex  capitalgain  \
0          Adm-clerical   Not-in-family   White   Male         2174
1       Exec-managerial         Husband   White   Male            0
2     Handlers-cleaners   Not-in-family   White   Male            0

   capitalloss  hoursperweek  native_country   Class
0            0            40   United-States   <=50K
1            0            13   United-States   <=50K
2            0            40   United-States   <=50K
```

In [65]:
```
#Do we have any missing data?
data.isnull().sum()
```

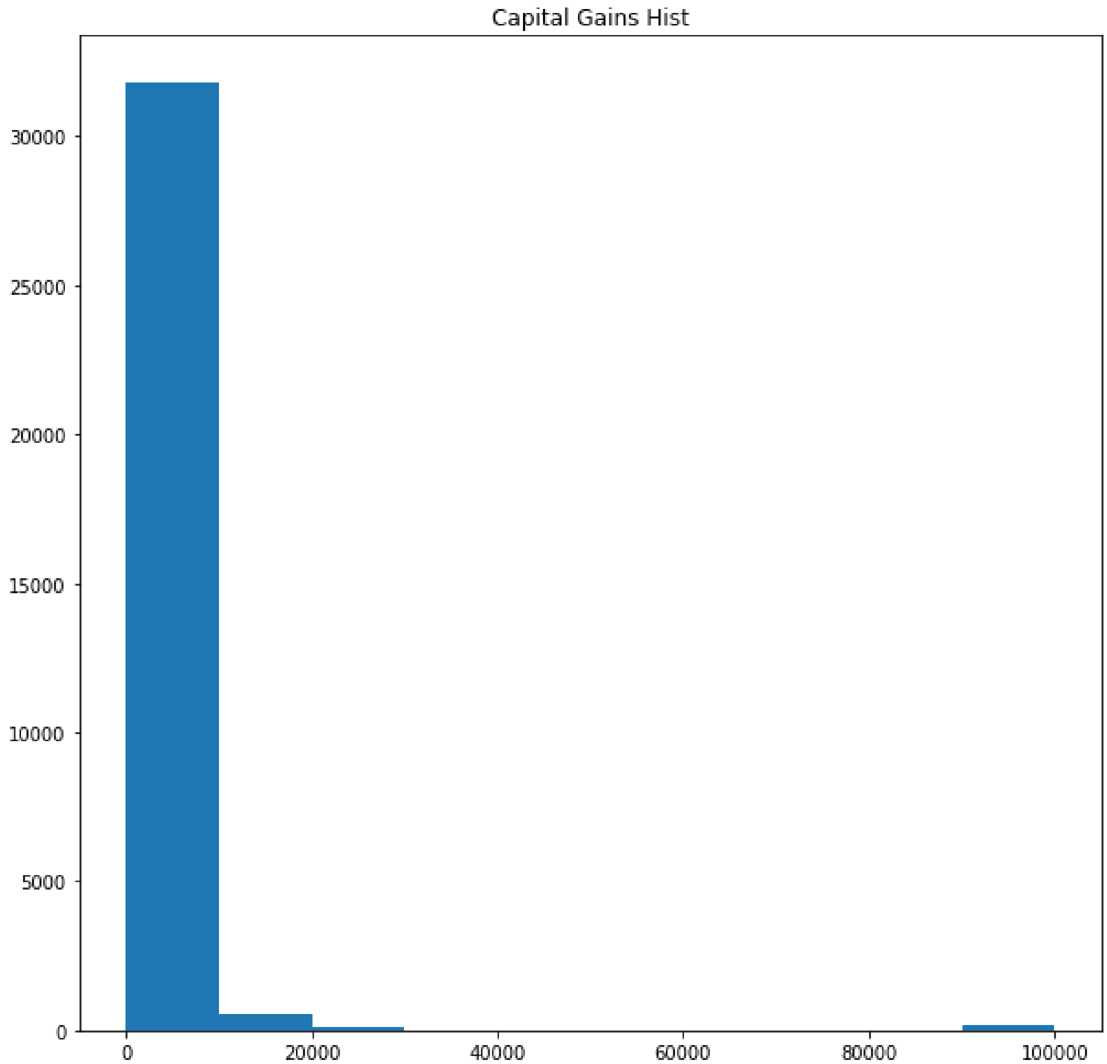
Out[65]:
```
Age               0
Workclass         0
education         0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
capitalgain       0
capitalloss       0
hoursperweek      0
native_country    0
Class             0
dtype: int64
```

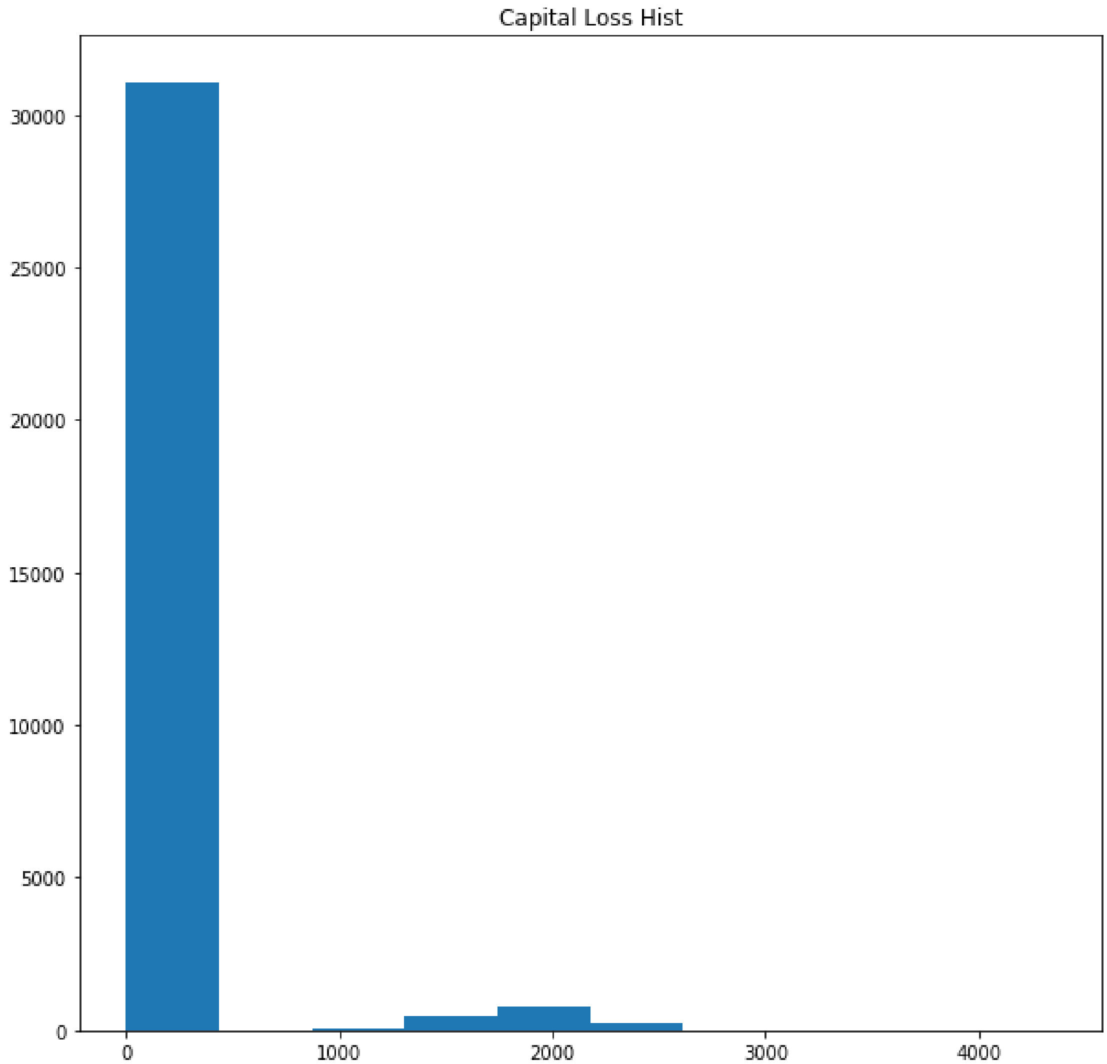
In [66]:
```
#Basic operations for feature engineering

data = pd.get_dummies(data, columns = ['Class'])
#Rename dummy columns for ease of indexing
data.rename(columns={'Class_ <=50K':'Below50'}, inplace=True)
data.rename(columns={'Class_ >50K':'Above50'}, inplace=True)
data['totalsamples'] = data['Below50'] + data['Above50'] #Sum samples
data['percent_below'] = data['Below50'] / data['totalsamples'] #Division on below thr
data['percent_above'] = data['Above50'] / data['totalsamples'] #Division on above thr
```

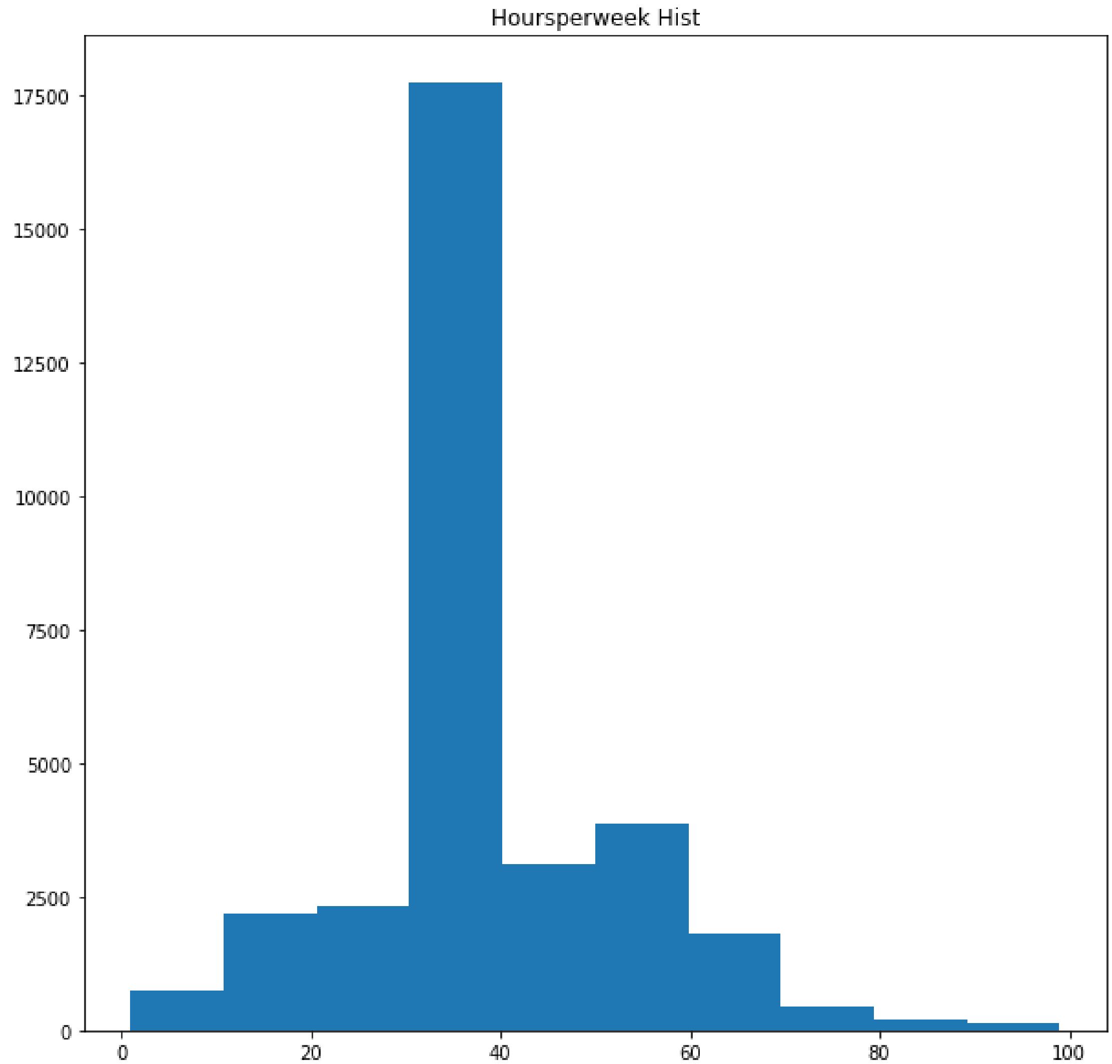
This data is highly structured and well put cleaned already. Summing the missing value counts above shows that we have no NaNs, and as such don't have to worry about dropping null values or imputing with a measure of central tendency

In [67]:
```
#Some basic plots to visualize data
from pylab import rcParams
rcParams['figure.figsize'] = 10, 10 #Resizing plots
import matplotlib.pyplot as plt
import seaborn as sns
plt.hist(data['capitalgain'])
plt.title('Capital Gains Hist')
```

```
plt.show()

plt.hist(data['capitalloss'])
plt.title('Capital Loss Hist')
plt.show()

plt.hist(data['hoursperweek'])
plt.title('Hoursperweek Hist')
plt.show()
```




Capital Loss Hist
30000
25000
20000
15000
10000
5000
0
0
1000
2000
3000
4000



Question 1: Let's start by showing the total count of samples within our dataset that belong to each grouping education.

In [68]:
```
#Get dummies for dependent Var == Class
data1 = data.copy()
#Pandas group by to show distribution
data1
```

Out[68]:
```
   Age         Workclass  education      marital_status  \
0   39         State-gov  Bachelors       Never-married
1   50  Self-emp-not-inc  Bachelors  Married-civ-spouse
2   38           Private    HS-grad            Divorced
3   53           Private       11th  Married-civ-spouse
4   28           Private  Bachelors  Married-civ-spouse
```

5	37	Private	Masters	Married-civ-spouse
6	49	Private	9th	Married-spouse-absent
7	52	Self-emp-not-inc	HS-grad	Married-civ-spouse
8	31	Private	Masters	Never-married
9	42	Private	Bachelors	Married-civ-spouse
10	37	Private	Some-college	Married-civ-spouse
11	30	State-gov	Bachelors	Married-civ-spouse
12	23	Private	Bachelors	Never-married
13	32	Private	Assoc-acdm	Never-married
14	40	Private	Assoc-voc	Married-civ-spouse
15	34	Private	7th-8th	Married-civ-spouse
16	25	Self-emp-not-inc	HS-grad	Never-married
17	32	Private	HS-grad	Never-married
18	38	Private	11th	Married-civ-spouse
19	43	Self-emp-not-inc	Masters	Divorced
20	40	Private	Doctorate	Married-civ-spouse
21	54	Private	HS-grad	Separated
22	35	Federal-gov	9th	Married-civ-spouse
23	43	Private	11th	Married-civ-spouse
24	59	Private	HS-grad	Divorced
25	56	Local-gov	Bachelors	Married-civ-spouse
26	19	Private	HS-grad	Never-married
27	54	?	Some-college	Married-civ-spouse
28	39	Private	HS-grad	Divorced
29	49	Private	HS-grad	Married-civ-spouse
...	...	...	...	...
32531	30	?	Bachelors	Never-married
32532	34	Private	Doctorate	Married-civ-spouse
32533	54	Private	Bachelors	Married-civ-spouse
32534	37	Private	Some-college	Divorced
32535	22	Private	12th	Never-married
32536	34	Private	Bachelors	Never-married
32537	30	Private	HS-grad	Never-married
32538	38	Private	Bachelors	Divorced
32539	71	?	Doctorate	Married-civ-spouse
32540	45	State-gov	HS-grad	Separated
32541	41	?	HS-grad	Separated
32542	72	?	HS-grad	Married-civ-spouse
32543	45	Local-gov	Assoc-acdm	Divorced
32544	31	Private	Masters	Divorced
32545	39	Local-gov	Assoc-acdm	Married-civ-spouse
32546	37	Private	Assoc-acdm	Divorced
32547	43	Private	HS-grad	Married-civ-spouse
32548	65	Self-emp-not-inc	Prof-school	Never-married
32549	43	State-gov	Some-college	Divorced
32550	43	Self-emp-not-inc	Some-college	Married-civ-spouse
32551	32	Private	10th	Married-civ-spouse
32552	43	Private	Assoc-voc	Married-civ-spouse

32553	32	Private	Masters	Never-married
32554	53	Private	Masters	Married-civ-spouse
32555	22	Private	Some-college	Never-married
32556	27	Private	Assoc-acdm	Married-civ-spouse
32557	40	Private	HS-grad	Married-civ-spouse
32558	58	Private	HS-grad	Widowed
32559	22	Private	HS-grad	Never-married
32560	52	Self-emp-inc	HS-grad	Married-civ-spouse

	occupation	relationship	race	sex \
0	Adm-clerical	Not-in-family	White	Male
1	Exec-managerial	Husband	White	Male
2	Handlers-cleaners	Not-in-family	White	Male
3	Handlers-cleaners	Husband	Black	Male
4	Prof-specialty	Wife	Black	Female
5	Exec-managerial	Wife	White	Female
6	Other-service	Not-in-family	Black	Female
7	Exec-managerial	Husband	White	Male
8	Prof-specialty	Not-in-family	White	Female
9	Exec-managerial	Husband	White	Male
10	Exec-managerial	Husband	Black	Male
11	Prof-specialty	Husband	Asian-Pac-Islander	Male
12	Adm-clerical	Own-child	White	Female
13	Sales	Not-in-family	Black	Male
14	Craft-repair	Husband	Asian-Pac-Islander	Male
15	Transport-moving	Husband	Amer-Indian-Eskimo	Male
16	Farming-fishing	Own-child	White	Male
17	Machine-op-inspct	Unmarried	White	Male
18	Sales	Husband	White	Male
19	Exec-managerial	Unmarried	White	Female
20	Prof-specialty	Husband	White	Male
21	Other-service	Unmarried	Black	Female
22	Farming-fishing	Husband	Black	Male
23	Transport-moving	Husband	White	Male
24	Tech-support	Unmarried	White	Female
25	Tech-support	Husband	White	Male
26	Craft-repair	Own-child	White	Male
27	?	Husband	Asian-Pac-Islander	Male
28	Exec-managerial	Not-in-family	White	Male
29	Craft-repair	Husband	White	Male
...	...	...	...	...
32531	?	Not-in-family	Asian-Pac-Islander	Female
32532	Prof-specialty	Husband	White	Male
32533	Exec-managerial	Husband	Asian-Pac-Islander	Male
32534	Adm-clerical	Unmarried	White	Female
32535	Protective-serv	Own-child	Black	Male
32536	Exec-managerial	Not-in-family	White	Female
32537	Craft-repair	Not-in-family	Black	Male

32538	Prof-specialty	Unmarried	Black	Female
32539	?	Husband	White	Male
32540	Adm-clerical	Own-child	White	Female
32541	?	Not-in-family	Black	Female
32542	?	Husband	White	Male
32543	Prof-specialty	Unmarried	White	Female
32544	Other-service	Not-in-family	Other	Female
32545	Adm-clerical	Wife	White	Female
32546	Tech-support	Not-in-family	White	Female
32547	Machine-op-inspct	Husband	White	Male
32548	Prof-specialty	Not-in-family	White	Male
32549	Adm-clerical	Other-relative	White	Female
32550	Craft-repair	Husband	White	Male
32551	Handlers-cleaners	Husband	Amer-Indian-Eskimo	Male
32552	Sales	Husband	White	Male
32553	Tech-support	Not-in-family	Asian-Pac-Islander	Male
32554	Exec-managerial	Husband	White	Male
32555	Protective-serv	Not-in-family	White	Male
32556	Tech-support	Wife	White	Female
32557	Machine-op-inspct	Husband	White	Male
32558	Adm-clerical	Unmarried	White	Female
32559	Adm-clerical	Own-child	White	Male
32560	Exec-managerial	Wife	White	Female

	capitalgain	capitalloss	hoursperweek	native_country	Below50 \
0	2174	0	40	United-States	1
1	0	0	13	United-States	1
2	0	0	40	United-States	1
3	0	0	40	United-States	1
4	0	0	40	Cuba	1
5	0	0	40	United-States	1
6	0	0	16	Jamaica	1
7	0	0	45	United-States	0
8	14084	0	50	United-States	0
9	5178	0	40	United-States	0
10	0	0	80	United-States	0
11	0	0	40	India	0
12	0	0	30	United-States	1
13	0	0	50	United-States	1
14	0	0	40	?	0
15	0	0	45	Mexico	1
16	0	0	35	United-States	1
17	0	0	40	United-States	1
18	0	0	50	United-States	1
19	0	0	45	United-States	0
20	0	0	60	United-States	0
21	0	0	20	United-States	1
22	0	0	40	United-States	1

23	0	2042	40	United-States	1
24	0	0	40	United-States	1
25	0	0	40	United-States	0
26	0	0	40	United-States	1
27	0	0	60	South	0
28	0	0	80	United-States	1
29	0	0	40	United-States	1
...	...	...	...	...	...
32531	0	0	99	United-States	1
32532	0	0	60	United-States	0
32533	0	0	50	Japan	0
32534	0	0	39	United-States	1
32535	0	0	35	United-States	1
32536	0	0	55	United-States	0
32537	0	0	46	United-States	1
32538	15020	0	45	United-States	0
32539	0	0	10	United-States	0
32540	0	0	40	United-States	1
32541	0	0	32	United-States	1
32542	0	0	25	United-States	1
32543	0	0	48	United-States	1
32544	0	0	30	United-States	1
32545	0	0	20	United-States	0
32546	0	0	40	United-States	1
32547	0	0	40	Mexico	1
32548	1086	0	60	United-States	1
32549	0	0	40	United-States	1
32550	0	0	50	United-States	1
32551	0	0	40	United-States	1
32552	0	0	45	United-States	1
32553	0	0	11	Taiwan	1
32554	0	0	40	United-States	0
32555	0	0	40	United-States	1
32556	0	0	38	United-States	1
32557	0	0	40	United-States	0
32558	0	0	40	United-States	1
32559	0	0	20	United-States	1
32560	15024	0	40	United-States	0

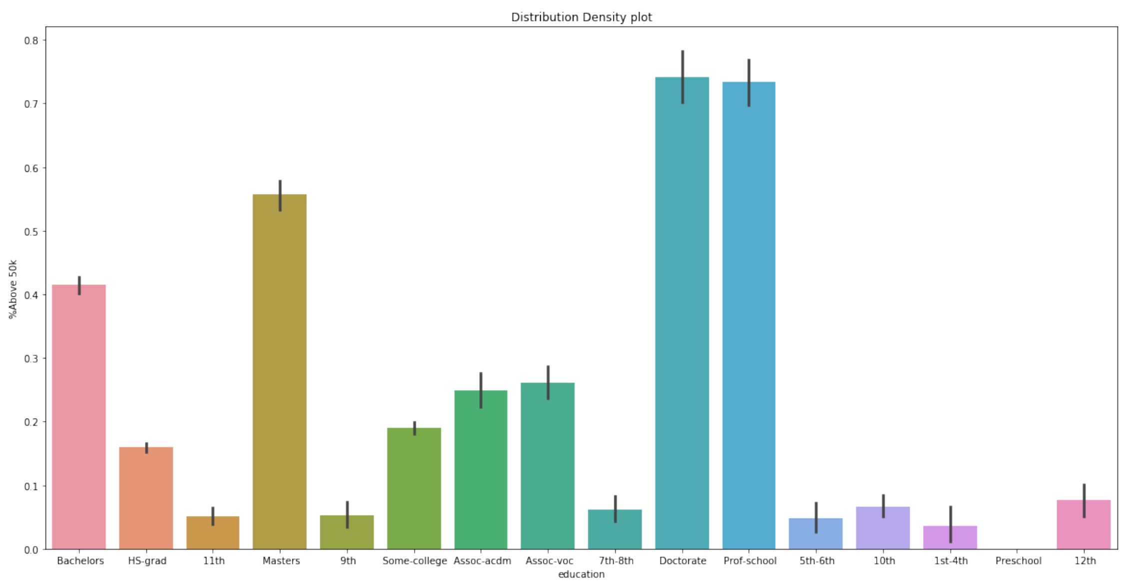
	Above50	totalsamples	percent_below	percent_above
0	0	1	1.0	0.0
1	0	1	1.0	0.0
2	0	1	1.0	0.0
3	0	1	1.0	0.0
4	0	1	1.0	0.0
5	0	1	1.0	0.0
6	0	1	1.0	0.0
7	1	1	0.0	1.0

8	1	1	0.0	1.0
9	1	1	0.0	1.0
10	1	1	0.0	1.0
11	1	1	0.0	1.0
12	0	1	1.0	0.0
13	0	1	1.0	0.0
14	1	1	0.0	1.0
15	0	1	1.0	0.0
16	0	1	1.0	0.0
17	0	1	1.0	0.0
18	0	1	1.0	0.0
19	1	1	0.0	1.0
20	1	1	0.0	1.0
21	0	1	1.0	0.0
22	0	1	1.0	0.0
23	0	1	1.0	0.0
24	0	1	1.0	0.0
25	1	1	0.0	1.0
26	0	1	1.0	0.0
27	1	1	0.0	1.0
28	0	1	1.0	0.0
29	0	1	1.0	0.0
...	...	...	...	...
32531	0	1	1.0	0.0
32532	1	1	0.0	1.0
32533	1	1	0.0	1.0
32534	0	1	1.0	0.0
32535	0	1	1.0	0.0
32536	1	1	0.0	1.0
32537	0	1	1.0	0.0
32538	1	1	0.0	1.0
32539	1	1	0.0	1.0
32540	0	1	1.0	0.0
32541	0	1	1.0	0.0
32542	0	1	1.0	0.0
32543	0	1	1.0	0.0
32544	0	1	1.0	0.0
32545	1	1	0.0	1.0
32546	0	1	1.0	0.0
32547	0	1	1.0	0.0
32548	0	1	1.0	0.0
32549	0	1	1.0	0.0
32550	0	1	1.0	0.0
32551	0	1	1.0	0.0
32552	0	1	1.0	0.0
32553	0	1	1.0	0.0
32554	1	1	0.0	1.0
32555	0	1	1.0	0.0

```
32556        0          1         1.0          0.0
32557        1          1         0.0          1.0
32558        0          1         1.0          0.0
32559        0          1         1.0          0.0
32560        1          1         0.0          1.0

[32561 rows x 17 columns]
```

In [69]:
```
#Barplot with percentage above 50k income
rcParams['figure.figsize'] = 20, 10
sns.barplot(x="education", y="Above50", data=data)
plt.title('Distribution Density plot')
plt.ylabel('%Above 50k')
```

Out[69]:
```
Text(0,0.5,'%Above 50k')
```



This table above really helps to show the distribution of our class variable against furthest education level. We can see taht a vast majority of the individuals who have completed high school as their last level of education are increasingly less likely to cross the 50k threshold which divideds our dependent variable.

In [70]:
```
#Get dummies for dependent Var == Class
data2 = data.copy()
#Pandas group by to show distribution
data2 =data2.groupby(['race', 'sex']).sum()
#colstodrop = ['Age','capitalgain','capitalloss','hoursperweek']
data2
```

Out[70]:
```
                                  Age  capitalgain  capitalloss  hoursperweek  \
race                    sex
```

```
 Amer-Indian-Eskimo  Female    4417         64808          1721          4353
                     Male      7144        129650          8908          8102
 Asian-Pac-Islander  Female   12141        269339         17595         12954
                     Male     27078       1266675         83419         28738
 Black               Female   58863        803303         70676         57277
                     Male     59124       1102151        117967         62756
 Other               Female    3453         27759          3955          3916
                     Male      5614        225534         12595          6780
 White               Female  318126       4957141        565105        313676
                     Male    760297      26242964       1960759        818132

                             Below50  Above50  totalsamples  percent_below  \
race                sex
 Amer-Indian-Eskimo  Female    107.0     12.0         119.0          107.0
                     Male      168.0     24.0         192.0          168.0
 Asian-Pac-Islander  Female    303.0     43.0         346.0          303.0
                     Male      460.0    233.0         693.0          460.0
 Black               Female   1465.0     90.0        1555.0         1465.0
                     Male     1272.0    297.0        1569.0         1272.0
 Other               Female    103.0      6.0         109.0          103.0
                     Male      143.0     19.0         162.0          143.0
 White               Female   7614.0   1028.0        8642.0         7614.0
                     Male    13085.0   6089.0       19174.0        13085.0

                             percent_above
race                sex
 Amer-Indian-Eskimo  Female           12.0
                     Male             24.0
 Asian-Pac-Islander  Female           43.0
                     Male            233.0
 Black               Female           90.0
                     Male            297.0
 Other               Female            6.0
                     Male             19.0
 White               Female         1028.0
                     Male           6089.0
```

Breaking it down by race and sex, which involves grouping on a passed listlike structure of vars, shows the above tabular output.

There is often talk of an income gap amongst races and genders, and this speaks a little bit to that point, although it could be a bit misleading. The total count of white males represented in this dataset are 19k/32k, which is right about 60% of the total. Class imbalance often lends itself to machine learning bias, from what I've read. Stratified sampling might be a better way break up the imbalance.

Even more interesting, however, is the fact that white males are not responsible for the biggest percent of race/sex over the threeshold - That belong to Asian-Pac-Islander males.

Question 2 Let's see if a combination of demographic data measured against hours worked shows us anything. Specifically, I want to look at all races/sexes for education level above a Bachelors to see if I can identify any disparities.

```
In [71]: #Get dummies for dependent Var == Class
         #Rename dummy columns for ease of indexing
         data3 = data.copy()
         #Filter the education column on a string match for secondary education
         data3 = data3[data3['education'].str.contains("Bachelors|Masters|Doctorate|Prof-Schoo
         #Pull out necessary columns
         data3 = data3[['education', 'race', 'sex', 'hoursperweek', 'Above50', 'Below50']]
         #Group by with a twist. Use .agg for calling specific measures against columns
         data3 = data3.groupby(['race', 'sex', 'education']).agg({'hoursperweek':'mean', 'Above
         #Same Ops as earlier for density
         data3['totalsamples'] = data3['Below50'] + data3['Above50'] #Sum samples
         data3['percent_below'] = data3['Below50'] / data3['totalsamples'] #Division on below
         data3['percent_above'] = data3['Above50'] / data3['totalsamples'] #Division on above
         data3
```

```
Out[71]:                                          hoursperweek  Above50  Below50  \
         race               sex    education
          Amer-Indian-Eskimo Female Bachelors        41.875000      3.0      5.0
                                   Doctorate        50.000000      1.0      1.0
                                   Masters          50.000000      2.0      0.0
                            Male   Bachelors        42.923077      5.0      8.0
                                   Doctorate        40.000000      1.0      0.0
                                   Masters          40.000000      1.0      2.0
          Asian-Pac-Islander Female Bachelors        39.949495     18.0     81.0
                                   Masters          37.352941      5.0     12.0
                            Male   Bachelors        42.084211     79.0    111.0
                                   Doctorate        44.964286     18.0     10.0
                                   Masters          40.647887     38.0     33.0
          Black              Female Bachelors        40.393939     27.0    138.0
                                   Doctorate        34.750000      3.0      1.0
                                   Masters          38.473684     15.0     23.0
                            Male   Bachelors        42.418182     69.0     96.0
                                   Doctorate        46.142857      6.0      1.0
                                   Masters          41.500000     25.0     23.0
          Other              Female Bachelors        38.142857      3.0     11.0
                                   Masters          37.000000      1.0      3.0
                            Male   Bachelors        45.000000      2.0     17.0
                                   Doctorate        45.000000      1.0      1.0
                                   Masters          40.000000      1.0      2.0
          White              Female Bachelors        39.148537    288.0   1045.0
                                   Doctorate        47.862500     46.0     34.0
                                   Masters          41.456842    156.0    319.0
                            Male   Bachelors        44.226933   1727.0   1622.0
                                   Doctorate        47.128028    230.0     59.0
```

		Masters	45.550847	715.0	347.0

race	sex	education	totalsamples	percent_below \
Amer-Indian-Eskimo	Female	Bachelors	8.0	0.625000
		Doctorate	2.0	0.500000
		Masters	2.0	0.000000
	Male	Bachelors	13.0	0.615385
		Doctorate	1.0	0.000000
		Masters	3.0	0.666667
Asian-Pac-Islander	Female	Bachelors	99.0	0.818182
		Masters	17.0	0.705882
	Male	Bachelors	190.0	0.584211
		Doctorate	28.0	0.357143
		Masters	71.0	0.464789
Black	Female	Bachelors	165.0	0.836364
		Doctorate	4.0	0.250000
		Masters	38.0	0.605263
	Male	Bachelors	165.0	0.581818
		Doctorate	7.0	0.142857
		Masters	48.0	0.479167
Other	Female	Bachelors	14.0	0.785714
		Masters	4.0	0.750000
	Male	Bachelors	19.0	0.894737
		Doctorate	2.0	0.500000
		Masters	3.0	0.666667
White	Female	Bachelors	1333.0	0.783946
		Doctorate	80.0	0.425000
		Masters	475.0	0.671579
	Male	Bachelors	3349.0	0.484324
		Doctorate	289.0	0.204152
		Masters	1062.0	0.326742

race	sex	education	percent_above
Amer-Indian-Eskimo	Female	Bachelors	0.375000
		Doctorate	0.500000
		Masters	1.000000
	Male	Bachelors	0.384615
		Doctorate	1.000000
		Masters	0.333333
Asian-Pac-Islander	Female	Bachelors	0.181818
		Masters	0.294118
	Male	Bachelors	0.415789
		Doctorate	0.642857
		Masters	0.535211
Black	Female	Bachelors	0.163636
		Doctorate	0.750000

```
                                     Masters        0.394737
                          Male       Bachelors      0.418182
                                     Doctorate      0.857143
                                     Masters        0.520833
 Other                    Female     Bachelors      0.214286
                                     Masters        0.250000
                          Male       Bachelors      0.105263
                                     Doctorate      0.500000
                                     Masters        0.333333
 White                    Female     Bachelors      0.216054
                                     Doctorate      0.575000
                                     Masters        0.328421
                          Male       Bachelors      0.515676
                                     Doctorate      0.795848
                                     Masters        0.673258
```

In [72]:
```
# Subset on just Bachelors
data4 = data.copy()
data4 = data4[data4['education'].str.contains("Bachelors")]
#Pull out necessary columns
data4 = data4[['education', 'race', 'sex', 'hoursperweek', 'Above50', 'Below50']]
#Group by with a twist. Use .agg for calling specific measures against columns
data4 = data4.groupby(['race', 'sex', 'education']).agg({'hoursperweek':'mean', 'Above
#Same Ops as earlier for density
data4['totalsamples'] = data4['Below50'] + data4['Above50'] #Sum samples
data4['percent_below'] = np.round(data4['Below50'] / data4['totalsamples'] * 100,2) #
data4['percent_above'] = np.round(data4['Above50'] / data4['totalsamples'] * 100,2) #

data4.sort_values(by= 'percent_above', ascending= False) #Sort desc
```

Out[72]:
```
                                             hoursperweek  Above50  Below50  \
race                sex     education
 White               Male    Bachelors        44.226933   1727.0   1622.0
 Black               Male    Bachelors        42.418182     69.0     96.0
 Asian-Pac-Islander  Male    Bachelors        42.084211     79.0    111.0
 Amer-Indian-Eskimo  Male    Bachelors        42.923077      5.0      8.0
                     Female  Bachelors        41.875000      3.0      5.0
 White               Female  Bachelors        39.148537    288.0   1045.0
 Other               Female  Bachelors        38.142857      3.0     11.0
 Asian-Pac-Islander  Female  Bachelors        39.949495     18.0     81.0
 Black               Female  Bachelors        40.393939     27.0    138.0
 Other               Male    Bachelors        45.000000      2.0     17.0

                                             totalsamples  percent_below  \
race                sex     education
 White               Male    Bachelors           3349.0          48.43
 Black               Male    Bachelors            165.0          58.18
 Asian-Pac-Islander  Male    Bachelors            190.0          58.42
```

```
 Amer-Indian-Eskimo  Male    Bachelors          13.0            61.54
                     Female  Bachelors           8.0            62.50
 White               Female  Bachelors        1333.0            78.39
 Other               Female  Bachelors          14.0            78.57
 Asian-Pac-Islander  Female  Bachelors          99.0            81.82
 Black               Female  Bachelors         165.0            83.64
 Other               Male    Bachelors          19.0            89.47

                                           percent_above
race                sex     education
 White               Male    Bachelors             51.57
 Black               Male    Bachelors             41.82
 Asian-Pac-Islander  Male    Bachelors             41.58
 Amer-Indian-Eskimo  Male    Bachelors             38.46
                     Female  Bachelors             37.50
 White               Female  Bachelors             21.61
 Other               Female  Bachelors             21.43
 Asian-Pac-Islander  Female  Bachelors             18.18
 Black               Female  Bachelors             16.36
 Other               Male    Bachelors             10.53
```

What I've done here is isolate people that have Bachelors degrees, as it's a bit more robust than looking at grouping of Masters and Doctorates. Similar operations were performed, and I sorted by the percent above > 50k.

I think this is a very interesting table for what it is, although there the data is not very representative of race splits in the US climate..

A few things of note: - White males w/ Bachelors degrees have the highest density dist./likelihood of making above 50k in the data sampled (Bach. Degrees). - The gap between white and black males with a Bachelors degree is not as supreme as one may have thought. - Women, although most of the total count skews toward white women, are not as equally represented amongst the proportion of people making over 50k with a Bachelors degree. - There seems to be some mild correlation between average hours worked per week and percent above the threshold. This analysis could likely be more thorough if raw salary numbers were included.

```
In [73]: #Modeling the data
         #Simple try catch for reading in the data.
         try:
             #Reading in the data
             data = 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data

             #Read in the data into a pandas df with column names (col names not included via
             data = pd.read_csv(data, names = ['Age', 'Workclass', 'finalweight', 'education',
                                  'occupation', 'relationship', 'race', 'sex', 'capitalga
                                  'hoursperweek', 'native_country', 'Class'])

         except:
             print('Something went wrong')
```

```
y = data['Class']
X = data
X.drop(columns= 'Class', inplace= True)
X = pd.get_dummies(X)
```

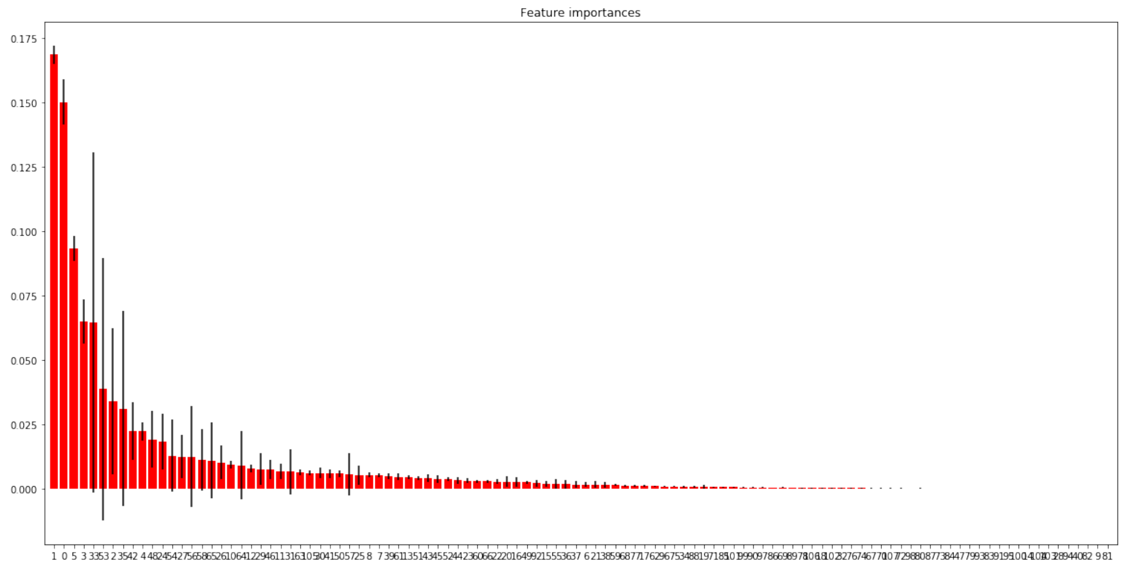
In [74]:
```
#Code borrowed from Sklearn Docs

print(__doc__)

import numpy as np
import matplotlib.pyplot as plt

from sklearn.datasets import make_classification
from sklearn.ensemble import ExtraTreesClassifier


# Build a forest and compute the feature importances
forest = ExtraTreesClassifier(n_estimators=250,
                              random_state=0)

forest.fit(X, y)
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(X.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plot the feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(X.shape[1]), indices)
plt.xlim([-1, X.shape[1]])
plt.show()
```

```
Automatically created module for IPython interactive environment
Feature ranking:
1. feature 1 (0.168577)
2. feature 0 (0.150220)
3. feature 5 (0.093361)
4. feature 3 (0.064950)
5. feature 33 (0.064662)
```

```
6. feature 53 (0.038794)
7. feature 2 (0.034152)
8. feature 35 (0.031232)
9. feature 42 (0.022425)
10. feature 4 (0.022382)
11. feature 48 (0.019236)
12. feature 24 (0.018491)
13. feature 54 (0.012907)
14. feature 27 (0.012613)
15. feature 56 (0.012560)
16. feature 58 (0.011205)
17. feature 65 (0.011127)
18. feature 26 (0.010309)
19. feature 10 (0.009506)
20. feature 64 (0.009100)
21. feature 12 (0.008005)
22. feature 29 (0.007700)
23. feature 46 (0.007654)
24. feature 11 (0.006954)
25. feature 31 (0.006730)
26. feature 63 (0.006388)
27. feature 105 (0.006290)
28. feature 30 (0.006195)
29. feature 41 (0.005964)
30. feature 50 (0.005958)
31. feature 57 (0.005762)
32. feature 25 (0.005456)
33. feature 8 (0.005446)
34. feature 7 (0.005210)
35. feature 39 (0.004987)
36. feature 61 (0.004786)
37. feature 13 (0.004611)
38. feature 51 (0.004348)
39. feature 43 (0.004223)
40. feature 45 (0.003933)
41. feature 52 (0.003846)
42. feature 44 (0.003366)
43. feature 23 (0.003198)
44. feature 60 (0.003051)
45. feature 66 (0.003006)
46. feature 22 (0.002902)
47. feature 20 (0.002836)
48. feature 16 (0.002783)
49. feature 49 (0.002661)
50. feature 92 (0.002239)
51. feature 15 (0.002095)
52. feature 55 (0.001950)
53. feature 36 (0.001894)
```

54. feature 37 (0.001811)
55. feature 6 (0.001747)
56. feature 21 (0.001714)
57. feature 38 (0.001629)
58. feature 59 (0.001506)
59. feature 68 (0.001275)
60. feature 77 (0.001238)
61. feature 17 (0.001105)
62. feature 62 (0.001085)
63. feature 96 (0.001058)
64. feature 75 (0.001020)
65. feature 34 (0.000974)
66. feature 88 (0.000885)
67. feature 19 (0.000835)
68. feature 71 (0.000805)
69. feature 85 (0.000802)
70. feature 101 (0.000719)
71. feature 99 (0.000625)
72. feature 90 (0.000621)
73. feature 97 (0.000609)
74. feature 86 (0.000534)
75. feature 69 (0.000530)
76. feature 89 (0.000499)
77. feature 78 (0.000393)
78. feature 106 (0.000390)
79. feature 18 (0.000370)
80. feature 102 (0.000365)
81. feature 32 (0.000364)
82. feature 76 (0.000351)
83. feature 74 (0.000347)
84. feature 67 (0.000301)
85. feature 70 (0.000289)
86. feature 107 (0.000288)
87. feature 72 (0.000248)
88. feature 98 (0.000227)
89. feature 80 (0.000222)
90. feature 87 (0.000214)
91. feature 73 (0.000199)
92. feature 84 (0.000184)
93. feature 47 (0.000184)
94. feature 79 (0.000178)
95. feature 93 (0.000148)
96. feature 83 (0.000144)
97. feature 91 (0.000120)
98. feature 95 (0.000117)
99. feature 100 (0.000102)
100. feature 14 (0.000100)
101. feature 104 (0.000091)

```
102. feature 103 (0.000081)
103. feature 28 (0.000054)
104. feature 94 (0.000039)
105. feature 40 (0.000018)
106. feature 82 (0.000012)
107. feature 9 (0.000002)
108. feature 81 (0.000000)
```



Top 5 feats.: 1. feature 1 (0.168577) - finalweight 2. feature 0 (0.150220) - age 3. feature 5 (0.093361) - hours per week 4. feature 3 (0.064950)- capital gain 5. feature 33 (0.064662) - marital_status_ Married-AF-spouse

This is essentially showing us the information gain/feature ranking of our independent vars in a tree based model architecture. It isn't incredibly well designed because I had to turn it into a sparse matrix to run the numerics with the categorical variables, but it is intuitive in letting us know that age and 'finalweight' are driving most of our inference ability. If we grouped/binned some of the cat vars better, we'd likely see different results. For the case of this assignment, there were no train test splits and the entire data set was modelled.

Most of what I've used here was not acquired (yet) from course lectures or asynch materials. I chose to use pandas because I was dealing with highly structured, tabular data, so there wasn't much need to deal with numpy arrays, lists or dicts.

One thing that I really don't like about using pandas dataframes is the difficulty that comes along with iterating through them. As we move along to unstructured data, particularly Json readins, I'm sure I'll be using a lot more of the aforementioned data structures for mapping/indexing and looping.

Appendix

- Percent Above Threshold computed by taking sum of counts of class > 50k/total samples.
- Percent Below Threshold computed by taking sum of counts of class < 50k/total samples.

References

- Sklearn Docs
- Pandas Docs
- Numpy Docs
- Stackoverflow