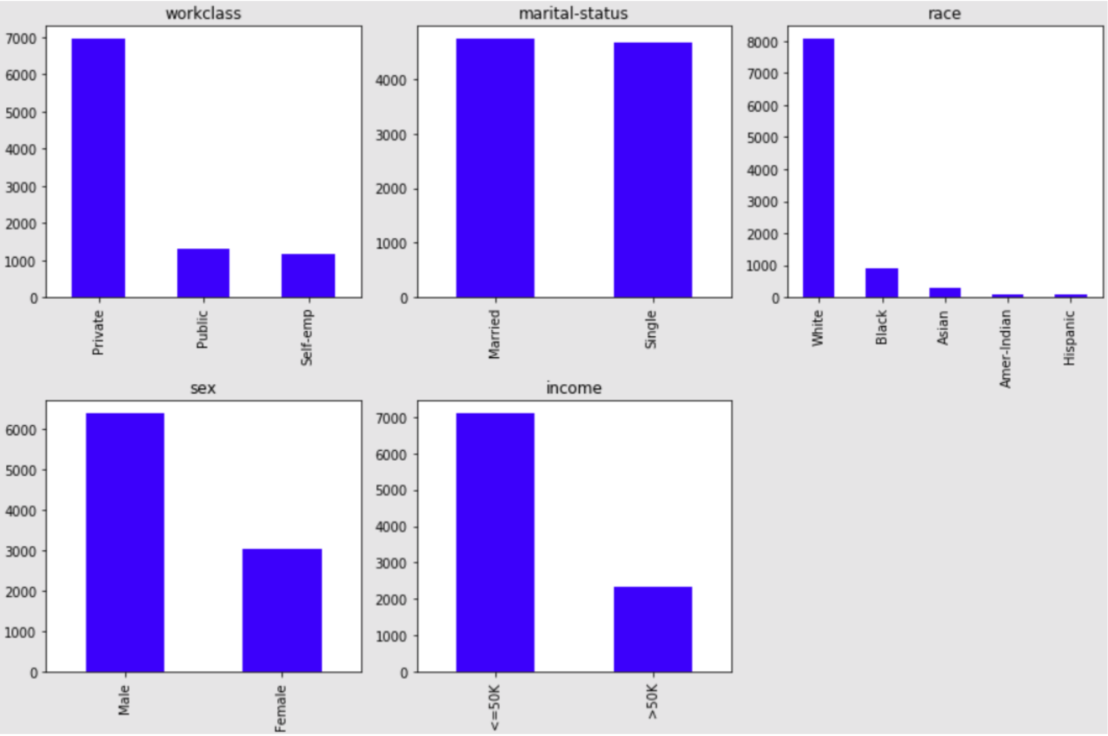
CSC 2611 Lab 6

For this lab you will experiment with Python. NumPy, and Pandas in order to perform some basic data preprocessing and exploratory analysis tasks. **You must only use Python, NumPy, Pandas, Matplotlib to perform the tasks for this lab.**

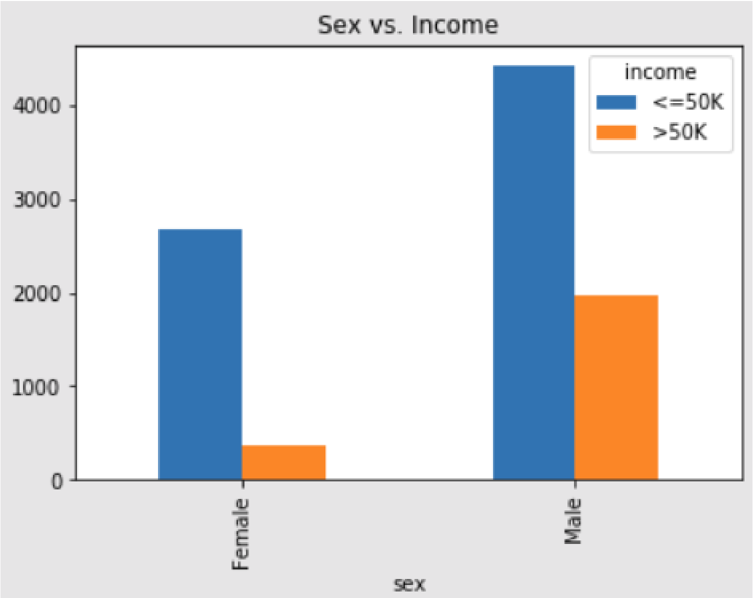
1. [10 pts] Download the data set *adult-modified.csv* and load it into an appropriate data structure such as a Pandas dataframe. Explore the general characteristics of the data as a whole: examine the means, standard deviations, and other statistics associated with the numeric attributes (Hint: use describe()) and frequencies associated with categorical attributes.

2. [10 pts] For the three numeric attributes (age, hours-per-week, education), display box plots that show the overall dispersion and skew in these variables. Next, create histograms for these three variables showing the overall data distribution in each. Finally, display a scatter plot of age (x-axis) vs. hours-per-week (y-axis).

3. [10 pts] For the remaining categorical attributes create bar charts that show the distribution of category frequencies (e.g., married vs. single; private vs. public vs. self-emp; etc). Ideally, you should use bar charts in a single figure like this figure.



4. [10 pts] Perform a cross-tabulations of each of the workclass and race attributes with the income attribute. Show the resulting cross-tab tables as well as bar charts to visualize the relationships between these pairs of attributes. [Hint: you can use aggregation functions in Pandas such as groupby() and cross-tab(), then either using Matplotlib directly or the plot() function in Pandas create the bar charts]. As an illustration, consider the graph below depicting the cross-tabulation of sex with income. In the case of race vs. income cross-tab, create another chart comparing the percentages of each race category that fall in the low-income group.



5. [10 pts] Compare and contrast the characteristics of the low-income and high-income categories across the different attributes. You may consider first creating separate subsets of the data based on the income categories and then characterizing each subset by observing summary statistics for each group across different variables. Discuss your observations focusing specifically on unique characteristics that seem to distinguish among the two groups. You may (though you are not required to) use charts or plots for visualizing the differences in your analysis.

6. [10 pts] Convert the data into the standard spreadsheet format. Note that this requires converting each categorical attribute into multiple binary ("dummy") attributes (one for each values of the categorical attribute) and assigning binary values corresponding to the presence or not presence of the attribute value in the original record). The numeric attributes should remain unchanged. Save this data in a new dataframe and show the top 10 rows in the new dataframe. Also save this new table into a local file called adult_numeric.csv.

7. [10 pts] Using the numeric data set with the dummy variables (of the previous part), perform basic correlation analysis among the attributes. You need to construct a complete Correlation Matrix (with rows and columns corresponding to each variable). [Hint: you can create the correlation matrix by using the corr() function in Pandas or corrcoef function in NumPy]. Next, using your correlation matrix, display in decreasing order of correlations, all attributes and their correlations to education. Repeat this step to display correlations with the attribute income_<=50K. Briefly discuss your general observations about this sample of adult population based on this correlation analysis.

8. [10 pts] Discretize the age attribute into 3 categories (corresponding to "young", "mid-age", and "old"). Do not change the original age attribute or add the discretized age to the table. Create a new dataframe with the numeric and the discretized age attributes as two columns and display the top 10 rows of the new dataframe.

9. [10 pts] Use Min-Max Normalization to transform the values of the attribute hours-per-week the range 0.0-1.0 (without changing the original data). Next, perform zscore normalization to standardize the values of all numeric attributes (age, hours-per-week, education). The latter step should be performed on all three attributes at the same time instead of one-by-one (you may wish to first create a separate dataframe with only these attributes and perform the operation on the whole dataframe. Note: for this problem, you should write your own code to perform the normalization; do not use pre-existing functions such as scikit-learn's MinMaxScaler(). Finally, show the top 10 rows of the three versions of the hours-per-week attribute (original, normalized, and standardized) side-by-side in a new dataframe.

10. [10 pts] Now download a modified version of the data (*adult-modified-missing-vals.csv*) that contains missing values. (a) Using Pandas determine

all the attributes with missing values and the number of missing values for each such attribute. (b) Show all the instances in the data that contain a missing value. (c) Fill the missing values for all numeric attributes using the mean value for the attribute. (d) After filling in the missing numeric values, drop all rows where a categorical attribute contains a missing value. (e) Show that the final resulting table does not contain missing values.