BuildModelingDataset

August 8, 2023

1 Assignment 2: Building a Modeling Data Set

[2]:
```
import os
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme()
```

In this assignment, you will complete the following tasks to build a modeling dataset:

1. Load the "adult" data set and identify the number of rows & columns
2. Build a new regression label column by winsorizing outliers
3. Replace all missing values with means
4. Identify two features with the highest correlation with label
5. Build appropriate bivariate plots between the highest correlated features and label

1.1 Part 1. Load the Data

Use the specified file name to load the data. Save it as a Pandas DataFrame called `df`.

Task: Read in the data using the `pd.read_csv()` function and save it to DataFrame `df`. Note: use the variable `filename` in your call to `pd.read_csv()`.

[3]:
```
# Do not remove or edit the line below:
filename = os.path.join(os.getcwd(), "data", "adult.data.full.asst")
```

[5]:
```
# YOUR CODE HERE
df=pd.read_csv(filename)
```

Task: Display the shape of `df` -- that is, the number of rows and columns.

[6]:
```
# YOUR CODE HERE
print(df.shape)
```

```
(32561, 15)
```

Check your work: while we used a small subset of the `adult` dataset in the exercises, the dataset that we are using now has a substantially greater number of rows, but the same number of columns as before. You should see this reflected when you print out the dimensions of DataFrame `df`.

Task: Get a peek of the data by displaying the first few rows, as you usually do.

[7]:
```
# YOUR CODE HERE
print(df.head())
```

```
    age         workclass  fnlwgt  education  education-num  \
0  39.0         State-gov   77516  Bachelors             13
1  50.0  Self-emp-not-inc   83311  Bachelors             13
2  38.0           Private  215646    HS-grad              9
3  53.0           Private  234721       11th              7
4  28.0           Private  338409  Bachelors             13

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

   capital-gain  capital-loss  hours-per-week native-country income_binary
0          2174             0            40.0  United-States         <=50K
1             0             0            13.0  United-States         <=50K
2             0             0            40.0  United-States         <=50K
3             0             0            40.0  United-States         <=50K
4             0             0            40.0           Cuba         <=50K
```

1.2 Part 2. Create a (Winsorized) Label Column

Assume that your goal is to use this dataset to fit a regression model that predicts the number of years of education that a person has had.

We'd like to create a new version of the `education-num` column, in which we replace the outlier values of `education-num` (on both sides of the range -- the low end as well as the high end). We will replace the outliers with the corresponding percentile value, as we did in the exercises. That is, if we wish to replace any value below, say, the 1.234-th percentile, we shall replace all such (various) values by the exact same value in our data -- the value such that 1.234% of data lies below it.

We will need to import the `stats` module from the `scipy` package:

[8]:
```
import scipy.stats as stats
```

Task: Create a new column, titled `label`, by winsorizing the `education-num` column with the top and bottom 1% percentile values.

[21]:
```
# YOUR CODE HERE
lower_limit=df['education-num'].quantile(.01)
upper_limit=df['education-num'].quantile(.99)
df['label']=df['education-num'].clip(lower_limit,upper_limit)
```

Let's verify that a new column got added to the DataFrame:

[22]:
```
df.head()
```

[22]:
```
    age         workclass  fnlwgt  education  education-num  \
0  39.0         State-gov   77516  Bachelors             13
1  50.0  Self-emp-not-inc   83311  Bachelors             13
2  38.0           Private  215646    HS-grad              9
3  53.0           Private  234721       11th              7
4  28.0           Private  338409  Bachelors             13

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

   capital-gain  capital-loss  hours-per-week native-country income_binary  \
0          2174             0            40.0  United-States         <=50K
1             0             0            13.0  United-States         <=50K
2             0             0            40.0  United-States         <=50K
3             0             0            40.0  United-States         <=50K
4             0             0            40.0           Cuba         <=50K

   label
0     13
1     13
2      9
3      7
4     13
```

An interesting thing to think about: take a look at the data and notice that for the first five rows, the values of the `education-num` column and its winsorized version -- `label` -- are the same. Does this mean that winsorization did not work? Or are there discrepancies further down the list of rows, where we cannot see them?

Task: Check that the values of `education-num` and `label` are *not* identical. You may do this by subtracting the two columns and then listing the unique values of the result. If you see values other than zero, it means *some* change did happen, as we would expect.

[24]:
```
# YOUR CODE HERE
difference=df['education-num']-df['label']
unique_values=difference.unique()
print(unique_values)
```

```
[ 0 -1 -2]
```

1.3 Part 3. Replace the Missing Values With Means

1.3.1 a. Identifying missingness

Task: Check if a given value in any data cell is missing, and sum up the resulting values (True/False) by columns. Assign the results to variable nan_count. Print the results.

[25]:
```
# YOUR CODE HERE
nan_count=df.isna().sum()
print(nan_count)
```

```
age                162
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex_selfID           0
capital-gain         0
capital-loss         0
hours-per-week     325
native-country     583
income_binary        0
label                0
dtype: int64
```

Replacing the missing values with the mean only makes sense for the numerically valued columns (and not for strings). Hence, we will focus on the age and hours-per-week columns.

1.3.2 b. Keeping record of the missingness: creating dummy variables

As a first step, you will now create dummy variables indicating missingness of the values.

Task: Store the True/False series that indicate missingness of any value in age as a new column called age_na. Store the True/False series that indicate missingness of every value of hours-per-week as a new column called hours-per-week_na.

[27]:
```
# YOUR CODE HERE
df['age_na']=df['age'].isna()
df['hours-per-week_na']=df['hours-per-week'].isna()
```

1.3.3 c. Replacing the missing values with mean values of the column

Task: Fill the missing values of the age and hours-per-week columns with the mean value of the corresponding column.

[32]:
```
# YOUR CODE HERE

df['age'].fillna(df['age'].mean(),inplace=True)
```

```
df['hours-per-week'].fillna(df['hours-per-week'].mean(),inplace=True)
```

Ungraded Task: Check your results. Display the sum of missing values for the age column (or reuse the code for listing total numbers of all missing values that you wrote before, if it worked.

[34]:
```
# YOUR CODE HERE - this cell will not be graded
age_missing_sum=df['age'].isna().sum()
print("Sum",age_missing_sum)
```

```
Sum 0
```

1.4 Part 4. Identify Features With the Highest Correlation With the Label

Your next goal is to figure out which features in the data correlate most with the label.

In the next few cells, we will demonstrate how to use Pandas `corr()` method to get a list of correlation coefficients between the `label` and all other (numerical) features. To learn more about the `corr()` method, consult the online documentation.

Let's first galnce at what the `corr()` method does:

[35]:
```
df.corr()
```

[35]:
```
                            age    fnlwgt  education-num  capital-gain  \
age                1.000000e+00 -0.076085       0.036685      0.124705
fnlwgt            -7.608468e-02  1.000000      -0.043195     -0.002234
education-num      3.668517e-02 -0.043195       1.000000      0.167089
capital-gain       1.247046e-01 -0.002234       0.167089      1.000000
capital-loss       5.747841e-02 -0.010252       0.079923     -0.055138
hours-per-week     6.657191e-02 -0.018047       0.146553      0.100995
label              3.854869e-02 -0.042134       0.999182      0.168202
age_na             7.101579e-18 -0.009015      -0.001709     -0.005314
hours-per-week_na -4.325250e-05 -0.005770      -0.005671      0.004981

                   capital-loss  hours-per-week     label        age_na  \
age                    0.057478    6.657191e-02  0.038549  7.101579e-18
fnlwgt                -0.010252   -1.804716e-02 -0.042134 -9.015193e-03
education-num          0.079923    1.465533e-01  0.999182 -1.708530e-03
capital-gain          -0.055138    1.009947e-01  0.168202 -5.313515e-03
capital-loss           1.000000    5.420158e-02  0.080453 -7.205893e-03
hours-per-week         0.054202    1.000000e+00  0.147275  2.254277e-03
label                  0.080453    1.472753e-01  1.000000 -1.955584e-03
age_na                -0.007206    2.254277e-03 -0.001956  1.000000e+00
hours-per-week_na     -0.001512    7.385613e-17 -0.005811 -2.709086e-03

                   hours-per-week_na
age                    -4.325250e-05
fnlwgt                 -5.769619e-03
education-num          -5.670679e-03
capital-gain            4.981172e-03
capital-loss           -1.511760e-03
hours-per-week          7.385613e-17
```

```
label                    -5.811006e-03
age_na                   -2.709086e-03
hours-per-week_na         1.000000e+00
```

The result is a computed *correlation matrix*. The values on the diagonal are all equal to 1, and the matrix is symmetrical with respect to the diagonal.

We only need to observe correlations of all features with the column `label` (as opposed to every possible pairwise correlation). Se let's query the `label` column of this matrix:

[36]:
```
df.corr()['label']
```

[36]:
```
age                  0.038549
fnlwgt              -0.042134
education-num        0.999182
capital-gain         0.168202
capital-loss         0.080453
hours-per-week       0.147275
label                1.000000
age_na              -0.001956
hours-per-week_na   -0.005811
Name: label, dtype: float64
```

This is good, but contains two values too many: we do not need to observe the correlation of `label` with itself, and moreover we are not interested in the correlation between the label and `education-num` (recall that `label` is a winsorized version of the `education-num`). So we will exclude these two values using the Pandas `drop()` method:

[37]:
```
exclude = ['label','education-num']
df.corr()['label'].drop(exclude, axis = 0)
```

[37]:
```
age                  0.038549
fnlwgt              -0.042134
capital-gain         0.168202
capital-loss         0.080453
hours-per-week       0.147275
age_na              -0.001956
hours-per-week_na   -0.005811
Name: label, dtype: float64
```

Task: The code below performs the same operation above, but saves the result to variable `corrs`. Sort the values in `corrs` in descending order. Use the Pandas method `sort_values()` to accomplish this task. For more information on how to use the `sort_values()` method, consult the online documentation.

[38]:
```
# Do not remove or edit the line below:
corrs = df.corr()['label'].drop(exclude, axis = 0)

corrs_sorted = corrs.sort_values(ascending=False)
```

Task: Save the *column names* for the top-2 correlation values into a Python list called `top_two_corr` *Tip*: `corrs_sorted` is a Pandas `Series` object, in which column names are the *index*. Once you find the column names, use the Python `list()` method to convert the values into a Python `list`.

[39]:
```
top_two_corr = list(corrs_sorted.head(2).index)
```

1.5 Part 5. Produce Bivariate Plots for the Label and Its Top Correlates

We will use the `pairplot()` function in `seaborn` to plot the relationships between the two features we identified and the label.

Task: Create a DataFrame named `df_sub` that contains only these three columns from DataFrame `df`: the label, and the two columns which correlate with it the most.

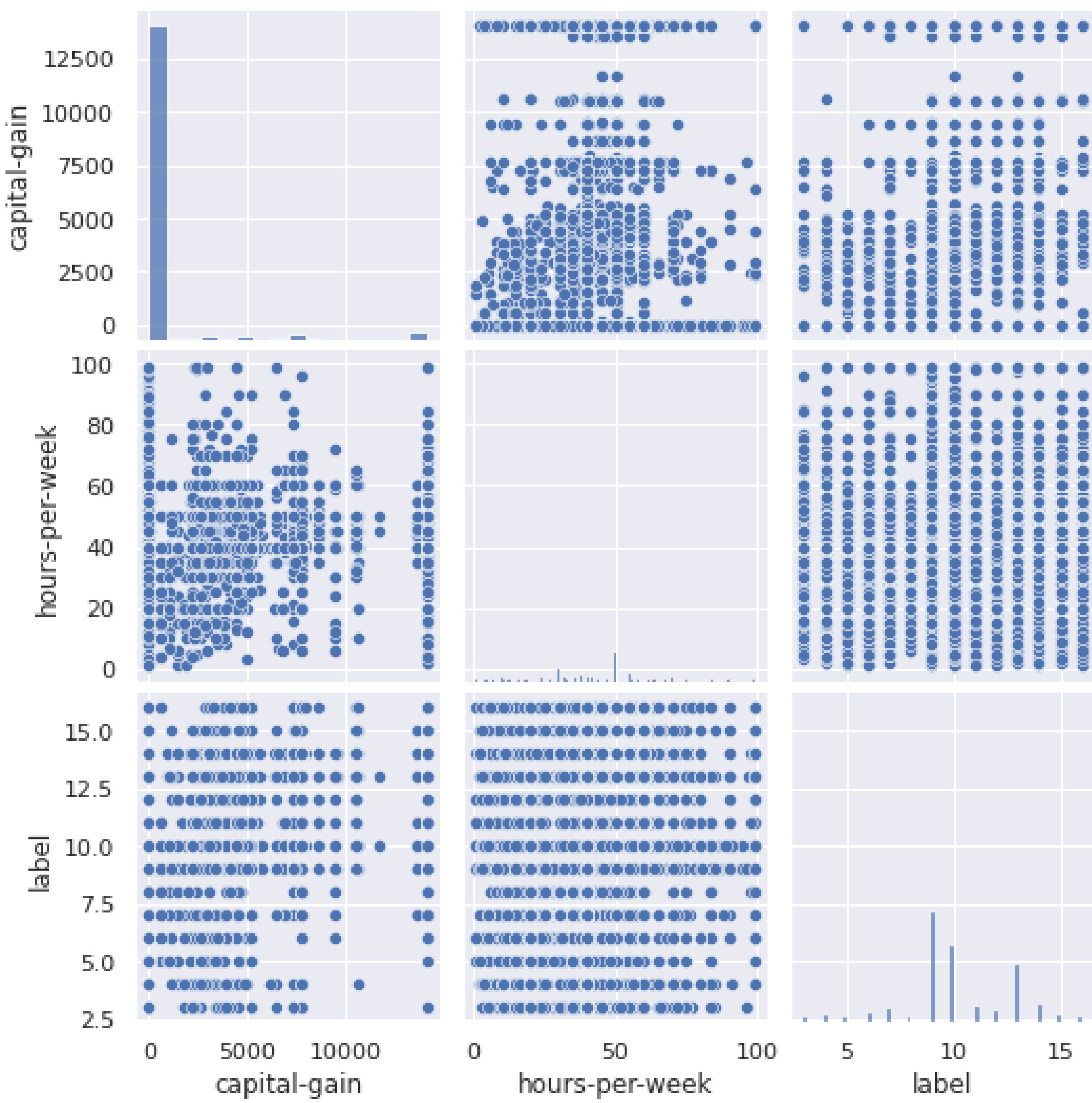
Tip: You can use the variable `top_two_corrs` in your solution.

[40]:
```
df_sub = df[top_two_corr+['label']]
```

Task: Create a `seaborn` pairplot of the data subset you just created.

[41]:
```
# YOUR CODE HERE
sns.pairplot(df_sub)
```

[41]: `<seaborn.axisgrid.PairGrid at 0x7f2482ccbd68>`



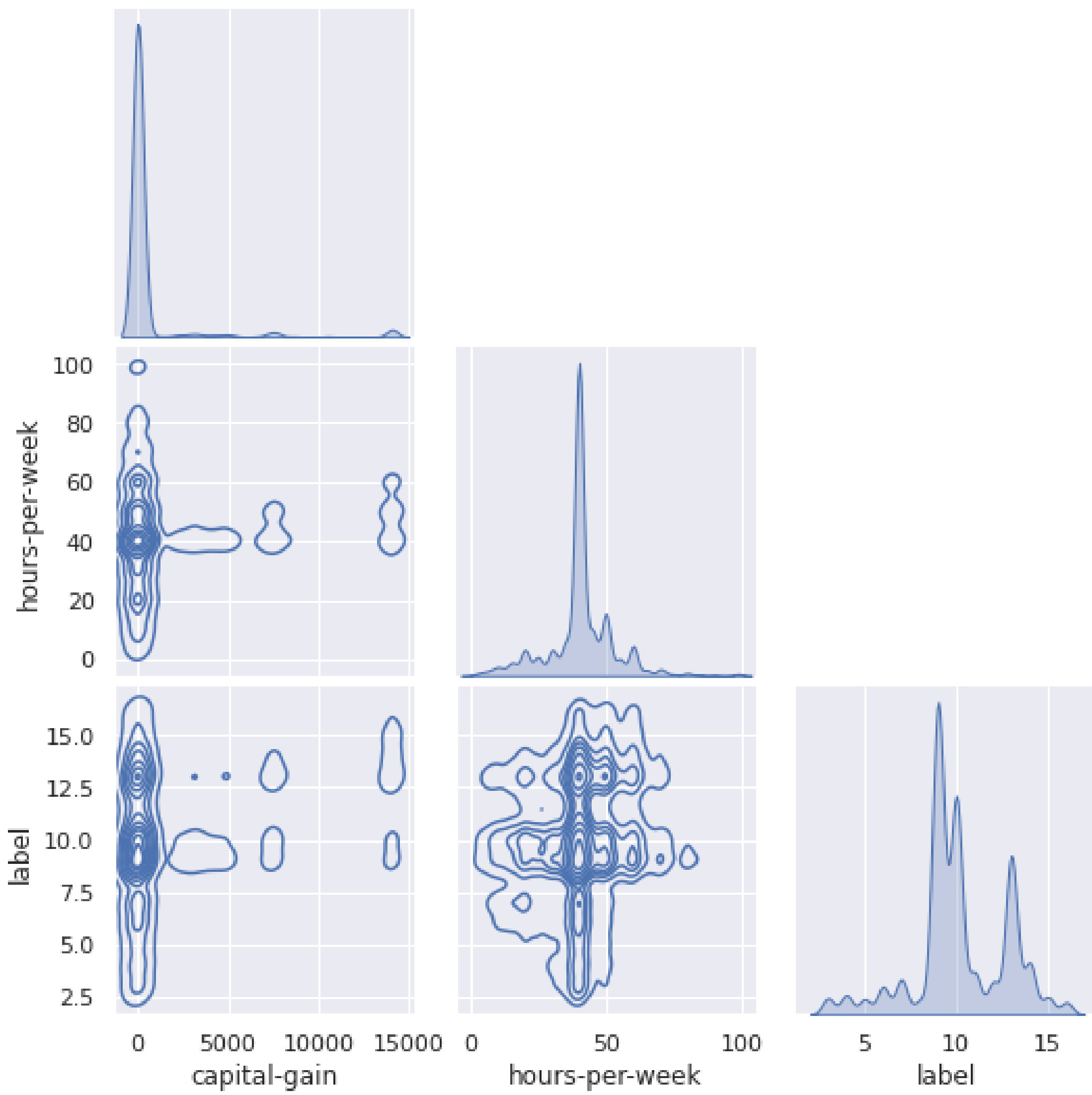
This one is not very easy to make sense of: the points overlap, but we do not have visibility into how densely they are stacked together.

Task: Repeat the `pairplot` exercise, this time specifying the *kernel density estimator* as the *kind* of the plot. *Tip*: Use `kind = 'kde'` as a parameter of the `pairplot()` function. You could also specify `corner=True` to make sure you don't plot redundant (symmetrical) plots.

Note: This will take a while to run and produce a plot.

[44]:
```
# YOUR CODE HERE
sns.pairplot(df_sub,kind='kde',corner=True)
```

[44]:
```
<seaborn.axisgrid.PairGrid at 0x7f24322d1dd8>
```



Think about the possible interpretations of these plots. (Recall that our label encodes `education`, in number of years). Here is an example of the kind of stories this data seems to be telling. It appears as though hours per week are stacked around the typical 40-hour value, and that this value of weekly hours dominates regardless of the level of education. However, it seems that it is somewhat less typical for people with lower levels of formal education to be working over 65 hours a week.

Analysis: Try to interpret what you see in this plot, as well as the one depicting the relationship between 'capital gain' and the levels of education, and see what kind of patterns you are noticing. Moreover, is there something odd that raises red flags and makes you think the data or our handling of it may be invalid? Is there something that, on the contrary, satisfies your intuition, thereby providing a 'sanity check'? These are the kind of questions that are useful to ask yourself as you are looking at the data distributions and pairwise relationships. Record your findings in the cell below.

These plots show that as someones education increases, as does their capital gain. However, a high increase in capital gain is not in the majority, with there still being a high concentration of capital gain towardsthe lower end of the spectrum. Because there is a large a large amount of points nearing the 0 end of capital gain, the data originally raised a red flag. However, looking at the hours-per-week plot, I notice a strong centralization around 40 hours of work a week throughout the data. This aligns with my intuition because a 40 hour week is the sytandard work week for a full time employee. In addition, there are some points of data ahowing less hours of work as well, but very little reaching towards 100 hours of work a week. This also makes sense, as there are only 168 hours in a week, so working close to the total asmount is unsustainable. However, lastly there is a correlation betwen larger amounts of education and slightly above 50 horus of work a week, what I interpret to be near 60 hours. This also makes sense, as often times people in research have to do work outside of the 9 to 5 standard work scedule. Also, many jobs do not pay by the hour, and instead have a standard salary for a year. Here, employees often have to work outside of the standard in order to complete their tasks.