Lab 1 Report:

Data Preparation Techniques for Machine Learning

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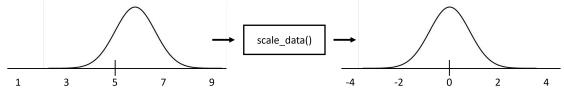
```
In [1]: # Import necessary libraries
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

In [2]: from IPython.display import Image # For displaying images in colab jupyter of the second colab part of the second colab part image.
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In [3]: Image('lab1_exercise1.png', width = 1000)

Out[3]:

O Exercise 1: Scaling Data with Standard Scaling



- In Machine Learning, the dataset is usually scaled ahead of time so that it is easier for the computer to learn and understand the problem.
- One of the most frequently used method is 'standard scaling', where the data is scaled by $z = (x \mu)/\sigma$. (x = original datapoint, $\mu =$ mean of the data, $\sigma =$ standard deviation)
- Write a function "scale_data()" which takes 2D NumPy array as an input and perform standard scaling on its columns. The function should output a new 2D array containing scaled column data.
- Test your function with selected columns in CMS calorimeter dataset (hgcal.csv).
- Plot the scaled dataset for the selected columns by using the provided matplotlib histogram function.

```
In [4]: # Load the dataset (.csv) using pandas package

CMS_calori_dataset = pd.read_csv('hgcal.csv')

# .head directive on the panda dataframe displays the first n-rows

CMS_calori_dataset.head(n = 10)
```

```
Out[4]:
            Unnamed:
                                        у
                                                                  phi
                                                                        energy trackId
                                                         eta
                       179.50383 -23.632137
                                             -7.878280 -0.0435 -0.130900
                                                                       0.200126
        0
                   0
                                                                                462412
         1
                       -143.63881 110.217940
                                            -72.706795
                                                      -0.3915
                                                              2.487094
                                                                       2.734594 493395
         2
                       179.50383
                                 -23.632120 -146.429610
                                                      -0.7395
                                                             -0.130900
                                                                       0.423910
                       -172.67310
                                 54.443620 -238.065340
                                                      -1.0875
                                                              2.836160
                                                                       0.713950 493640
         3
         4
                    4 -180.88046
                                 7.897389 -238.065340
                                                      -1.0875
                                                              3.097959
                                                                      0.000000 495225
         5
                    5 -180.88045
                                 -7.897438 -238.065340
                                                      -1.0875
                                                              -3.097959
                                                                       0.034491 495225
        6
                    6 -152.69838 -97.279590 -265.020540
                                                      -1.1745
                                                              -2.574361
                                                                       0.580138 460126
         7
                        -23.63213 179.503810
                                           -325.172060
                                                      -1.3485
                                                              1.701696
                                                                       0.411487 465028
        8
                       -152.69835
                                  97.279594
                                                       0.4785
                                                              2.574361
                                                                        0.183141
                                                                                  1383
                                             89.977780
                       -176.76110
                                  39.187016
                                            107.930240
                                                       0.5655
                                                              2.923426
                                                                       0.337551
                                                                                  4421
In [5]: # Convert the panda dataframe into numpy 2D array
        CMS calori dataset np = CMS calori dataset.to numpy()
        #print(CMS calori dataset np)
        # The converted numpy array has the dimension of 420 (rows) x 8 (columns)
        print(CMS calori dataset np.shape)
       (420, 8)
In [6]: # Extract only x, y, z, eta, phi and energy columns from the dataset and sta
        # Name this new 2D array CMS calori dataset np sub.
        # The array should have dimension 420 (rows) x 6 (columns)
        CMS calori dataset np sub = CMS calori dataset np[:,1:-1] # data extraction
        print(CMS calori dataset np sub.shape)
       (420, 6)
In [7]: # Create the scaling function
        # this does the assigned mathematical function elementwise on arr.
        # However it expects a specific array shape and will break if given wrong sh
        def scale data(arr):
             scaled data = []
                                # init empty list
             dim = arr.shape[1] # get the number of columns
             for i in range(dim): # for each data type (x, y, z, etc.) apply respecti
                 mean = np.mean(arr[:, i])
                 std = np.std(arr[:, i])
                 temp arr = (arr[:, i] - mean) / std
                 scaled data.append(temp arr) # fill empty list
             scaled data = np.array(scaled data) # convert list to array
             return np.transpose(scaled data) # transpose the array to get the correct
In [8]: # Test the function with CMS calori dataset np sub
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```
CMS_calori_dataset_np_sub_scaled = scale_data(CMS_calori_dataset_np_sub)
print(CMS_calori_dataset_np_sub_scaled[0])
```

 $\hbox{ [1.91214438 -0.51027049 -0.44193343 -0.47341363 -0.31488841 -0.38410307] } \\$

```
In [9]: # Confirm the data is scaled for 'x' column

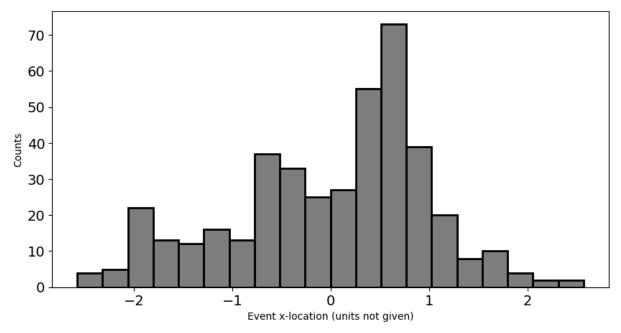
plt.figure(figsize = (10, 5))

plt.hist(CMS_calori_dataset_np_sub_scaled[:, 0], bins = 20, facecolor = 'greplt.xticks(fontsize=14)

plt.yticks(fontsize=14)

plt.xlabel('Event x-location (units not given)') # Units not given in assignplt.ylabel('Counts')

plt.show()
```



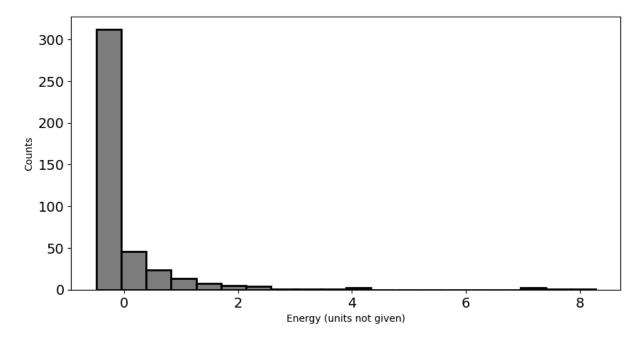
```
In [10]: # Confirm the data is scaled for 'energy' column

plt.figure(figsize = (10, 5))

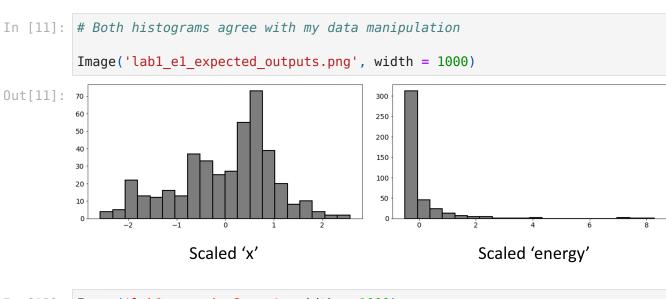
plt.hist(CMS_calori_dataset_np_sub_scaled[:, 5], bins = 20, facecolor = 'greplt.xticks(fontsize=14)
    plt.yticks(fontsize=14)

plt.xlabel('Energy (units not given)')
plt.ylabel('Counts')

plt.show()
```



Expected histogram outputs - Feel free to style your plot differently

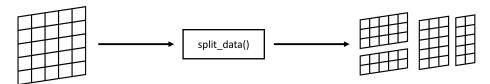


In [12]: Image('lab1_exercise2.png', width = 1000)

Out[12]:



Exercise 2: Data Splitting



- In this exercise you will write a function called split_data() which given a NumPy array, it splits the array into sub-arrays.
- Data splitting is used to divide the dataset into training, validation and testing sets, which we will describe in later lab.
- The function should take following parameters
 - arr 2D NumPy array representing a dataset
 - split_proportions a list containing split ratios, e.g., [0.2, 0.3, 0.5]
 - axis a direction to be splitted (0 = row-wise, 1 = column-wise)
- Test your function on the scaled dataset from exercise 1 with given parameters in the lab template.
- · Confirm that your sub arrays have correct dimensions by printing their shape

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In [13]: # Create the splitting function
         # Wrote this before I knew about np.split
         def split data(arr, split proportions, axis):
             if not np.isclose(np.sum(split proportions), 1): # make sure split pr
                 raise ValueError("Try again. The sum of split proportions must be ed
             # normalize proportions to array size. Convert to int for indexing
             slice sizes = (np.array(split proportions) * arr.shape[axis]).astype(int
             slice sizes = slice sizes[:-1] # last element not needed in loop
                                    # init empty list to be filled by for loop
             split data list = []
             for i in slice sizes:
                 if axis == 0: # make sure slicing syntax is correct for desired axis
                     temp arr = arr[:i,:] # grab specified portion
                     arr = arr[i:,:] # remove the grabbed portion from the original a
                                     # that next iteration can also start from beginn
                 else:
                     temp arr = arr[:,:i]
                     arr = arr[:,i:]
                 split data list.append(temp arr) # fill the list with the sliced da
             split data list.append(arr) # append the leftover portion to the split d
             return split data list
         # This is a better way of doing the same thing but I kept the above function
         def split data numpy(arr, split proportions, axis):
             # normalize proportions to array size. Convert to int for indexing
             if not np.isclose(np.sum(split proportions), 1):
                 raise ValueError("Try again. The sum of split proportions must be ed
             # Convert proportions to index numbers of the source array. eq. [0.2, 0.
             indices = (np.cumsum(np.array(split proportions)) * arr.shape[axis]).ast
```

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indices = indices[:-1] # last element not needed
             split data list = np.split(arr, indices, axis=axis) # nice and easy nump
             return split data list
In [14]: # Test your split function against scaled CMS Calorimieter dataset from exer
         sub data list 1 = split data(arr = CMS_calori_dataset_np_sub_scaled,
                                              split proportions = [0.6, 0.2, 0.2], axi
In [15]: # Confirm that dataset has been split into correct shapes
         # The correct dimensions should be (252, 6) (84, 6) (84, 6)
         print(sub data list 1[0].shape, sub data list 1[1].shape, sub data list 1[2]
        (252, 6) (84, 6) (84, 6)
In [16]: # Test your split function against scaled CMS Calorimieter dataset from exer
         sub data list 2 = split data(arr = CMS calori dataset np sub scaled,
                                                          split proportions = [0.5, 0.
In [17]: # Confirm that dataset has been split into correct shapes
         # The correct dimensions should be (420, 3) (420, 3)
         print(sub data list 2[0].shape, sub data list 2[1].shape)
        (420, 3) (420, 3)
 In [ ]:
 In [ ]:
```