IQRA University

CSC 471 Artificial Intelligence

Lab# 09

ML Libraries and Data Processing

Objective:

This lab introduces the students to some popular and frequently used machine learning libraries. The students are also provided some insight into the data handling and preprocessing steps involved before any supervised learning task.

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Date of Experiment: ______________________________

Introduction to NumPy

This lab outlines techniques for effectively loading, storing, and manipulating in-memory data in Python. The topic is very broad: datasets can come from a wide range of sources and a wide range of formats, including collections of documents, collections of images, collections of sound clips, collections of numerical measurements, or nearly anything else. Despite this apparent heterogeneity, it will help us to think of all data fundamentally as arrays of numbers.

For example, images–particularly digital images–can be thought of as simply two-dimensional arrays of numbers representing pixel brightness across the area. Sound clips can be thought of as one-dimensional arrays of intensity versus time. Text can be converted in various ways into numerical representations, perhaps binary digits representing the frequency of certain words or pairs of words. No matter what the data are, the first step in making it analyzable will be to transform them into arrays of numbers. (We will discuss some specific examples of this process later in Feature Engineering)

For this reason, efficient storage and manipulation of numerical arrays is absolutely fundamental to the process of doing data science. We'll now take a look at the specialized tools that Python has for handling such numerical arrays: the NumPy package, and the Pandas package.

The notebooks provided along with this lab will cover NumPy in detail. NumPy (short for *Numerical Python*) provides an efficient interface to store and operate on dense data buffers. In some ways, NumPy arrays are like Python's built-in list type, but NumPy arrays provide much more efficient storage and data operations as the arrays grow larger in size. NumPy arrays form the core of nearly the entire ecosystem of data science tools in Python, so time spent learning to use NumPy effectively will be valuable no matter what aspect of data science interests you.

Data Manipulation with Pandas

NumPy provides efficient storage and manipulation of dense typed arrays in Python. Next, we'll build on this knowledge by looking in detail at the data structures provided by the Pandas library.

Pandas is a newer package built on top of NumPy, and provides an efficient implementation of a DataFrame. DataFrames are essentially multidimensional arrays with attached row and column labels, and often with heterogeneous types and/or missing data. As well as offering a convenient storage interface for labeled data, Pandas implements a number of powerful data operations familiar to users of both database frameworks and spreadsheet programs.

As we saw, NumPy's ndarray data structure provides essential features for the type of clean, wellorganized data typically seen in numerical computing tasks. While it serves this purpose very well, its limitations become clear when we need more flexibility (e.g., attaching labels to data, working with missing data, etc.) and when attempting operations that do not map well to element-wise broadcasting (e.g., groupings, pivots, etc.), each of which is an important piece of analyzing the less structured data available in many forms in the world around us. Pandas, and in particular its Series and DataFrame objects, builds on the NumPy array structure and provides efficient access to these sorts of "data munging" tasks that occupy much of a data scientist's time.

In this chapter, we will focus on the mechanics of using Series, DataFrame, and related structures effectively. We will use examples drawn from real datasets where appropriate, but these examples are not necessarily the focus.

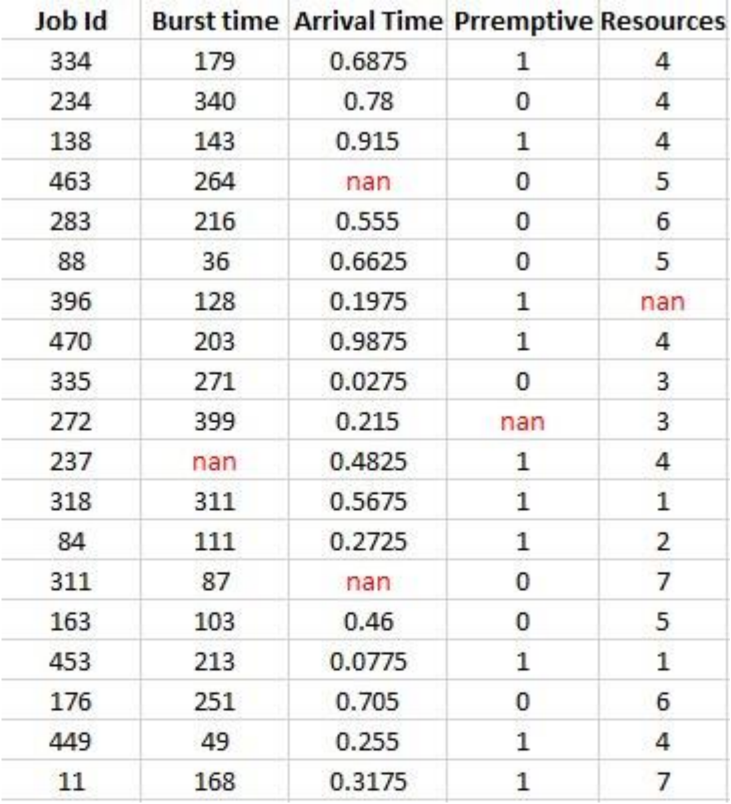
Data Pre-processing

Data scientists come across many datasets and not all of them may be well formatted or noise free. While doing any kind of analysis with data it is important to clean it, as raw data can be highly unstructured with noise or missing data or data that is varying in scales which makes it hard to extract useful information. Pre-processing refers to the transformations applied to our data before feeding it to any machine learning algorithm. It is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis

There are different techniques of data preprocessing some of which will be covered in this lab:

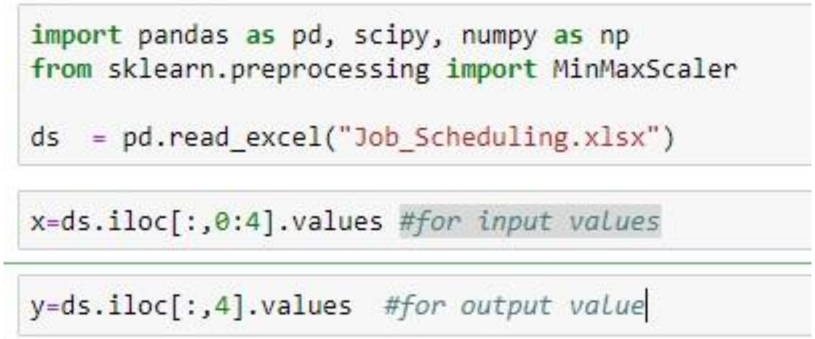
Data Loading

In order to implement data pre-processing, first we need to load the raw dataset. In this lab, we will be using a sample dataset of CPU job scheduling as shown below:



Job Id	Burst time	Arrival Time	Prremptive	Resources
334	179	0.6875	1	4
234	340	0.78	0	4
138	143	0.915	1	4
463	264	nan	0	5
283	216	0.555	0	6
88	36	0.6625	0	5
396	128	0.1975	1	nan
470	203	0.9875	1	4
335	271	0.0275	0	3
272	399	0.215	nan	3
237	nan	0.4825	1	4
318	311	0.5675	1	1
84	111	0.2725	1	2
311	87	nan	0	7
163	103	0.46	0	5
453	213	0.0775	1	1
176	251	0.705	0	6
449	49	0.255	1	4
11	168	0.3175	1	7

To load this dataset into our application, we need to write a simple set of commands as:



```
import pandas as pd, scipy, numpy as np
from sklearn.preprocessing import MinMaxScaler

ds  = pd.read_excel("Job_Scheduling.xlsx")
```

```
x=ds.iloc[:,0:4].values #for input values
```

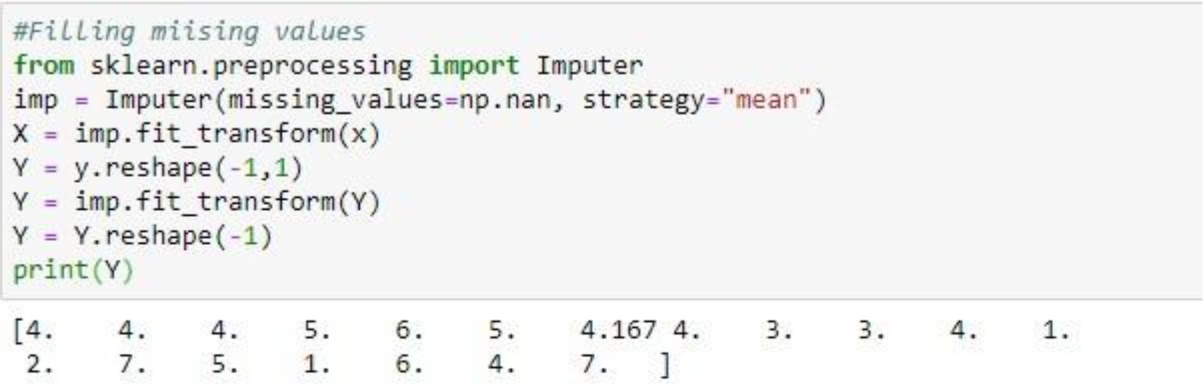
```
y=ds.iloc[:,4].values  #for output value
```

1. Dealing with Missing Data

We have some missing fields in the data denoted by “nan” which is an acronym for “not a number”. Machine learning models cannot accommodate missing fields in the data they are provided with. So, the missing fields must be filled with values that will not affect the variance of the data and make it less noisy.

The sklearn.impute python library contains SimpleImputer class that provides basic strategies for imputing missing values. Missing values can be imputed with a provided constant value, or using the statistics (mean, median or most frequent) of each column in which the missing values are located. This class also allows for different missing values encodings.

The following snippet demonstrates how to replace missing values, encoded as np.nan, using the mean value of the columns (axis 0) that contain the missing values:



```
#Filling miising values
from sklearn.preprocessing import Imputer
imp = Imputer(missing_values=np.nan, strategy="mean")
X = imp.fit_transform(x)
Y = y.reshape(-1,1)
Y = imp.fit_transform(Y)
Y = Y.reshape(-1)
print(Y)
```

```
[4.    4.    4.    5.    6.    5.    4.167 4.    3.    3.    4.    1.
 2.    7.    5.    1.    6.    4.    7.   ]
```

The SimpleImputer class also supports categorical data represented as string values or pandas categoricals when using the 'most_frequent' or 'constant' strategy:

```
import pandas as pd df =
pd.DataFrame([["a", "x"],
[np.nan, "y"],
                   ["a", np.nan],
                   ["b", "y"]], dtype="category")

imp = SimpleImputer(strategy="most_frequent")
print(imp.fit_transform(df))
```

The following snippet demonstrates how to replace missing values, encoded as np.nan, using the mean feature value of the two nearest neighbors of samples with missing values:

```
import numpy as np
from sklearn.impute import KNNImputer nan
= np.nan
X = [[1, 2, nan], [3, 4, 3], [nan, 6, 5], [8, 8, 7]] imputer
= KNNImputer(n_neighbors=2, weights="uniform")
imputer.fit_transform(X)
```

NaN is usually used as the placeholder for missing values. However, it enforces the data type to be float. The parameter missing_values allows to specify other placeholder such as integer. In the following example, we will use -1 as missing values:

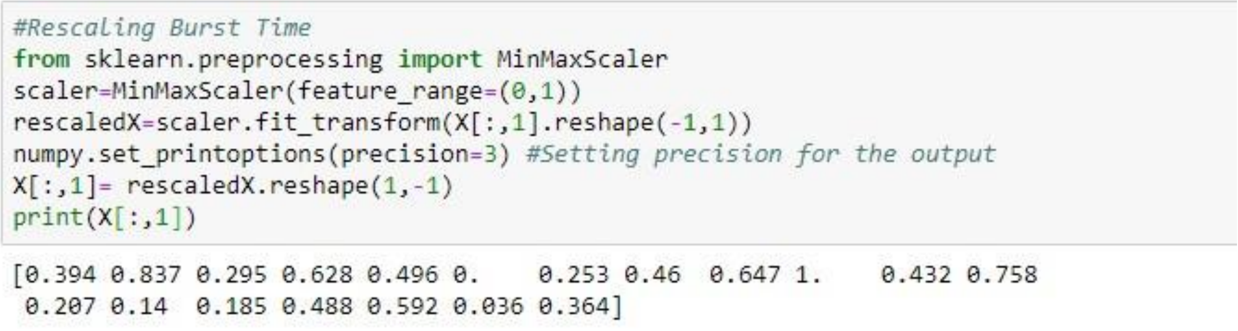
```
from sklearn.impute import MissingIndicator
X = np.array([[-1, -1, 1, 3],
              [4, -1, 0, -1],
[8, -1, 1, 0]])
indicator = MissingIndicator(missing_values=-1)
mask_missing_values_only = indicator.fit_transform(X)
mask_missing_values_only
```

2. Rescale Data

When the data is comprised of attributes with varying scales, many machine learning algorithms can benefit from rescaling the attributes to all have the same scale. It is also useful for algorithms that weight inputs like regression and neural networks and algorithms that use distance measures like K-Nearest Neighbors. Data can be rescaled using scikit-learn using the MinMaxScaler class.

$$v'_i = (\underline{\qquad\qquad\qquad}\mathbf{max}(v^i - v_i^{\mathbf{min}} - \mathbf{min}^{f()}(v_{i_v})_i) \times (high - low) + low$$

Let us rescale the job burst time into the range of 0 and 1:

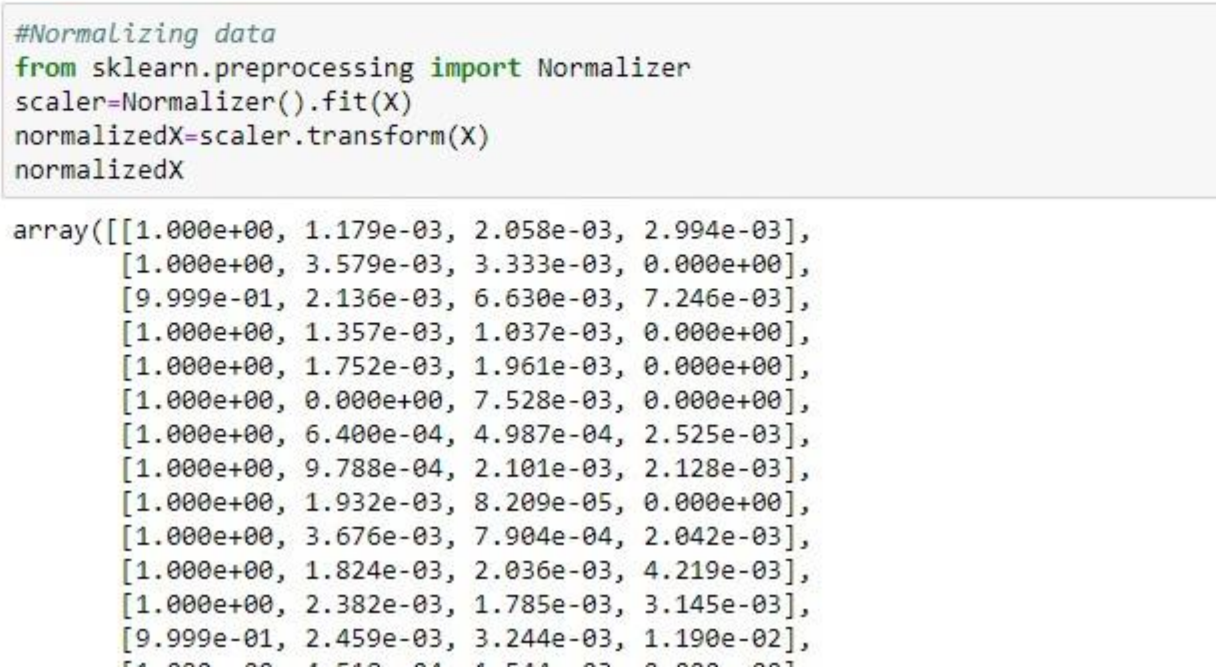


```
#Rescaling Burst Time
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
rescaledX=scaler.fit_transform(X[:,1].reshape(-1,1))
numpy.set_printoptions(precision=3) #Setting precision for the output
X[:,1]= rescaledX.reshape(1,-1)
print(X[:,1])
```

```
[0.394 0.837 0.295 0.628 0.496 0.    0.253 0.46  0.647 1.    0.432 0.758
 0.207 0.14  0.185 0.488 0.592 0.036 0.364]
```

3. Normalization

Normalization involves adjusting the values in the feature vector so as to measure them on a common scale. Here, the values of a feature vector are adjusted so that they sum up to 1. Normalization is used to ensure that data points do not get boosted due to the nature of their features.



```
#Normalizing data
from sklearn.preprocessing import Normalizer
scaler=Normalizer().fit(X)
normalizedX=scaler.transform(X)
normalizedX
```

```
array([[1.000e+00, 1.179e-03, 2.058e-03, 2.994e-03],
       [1.000e+00, 3.579e-03, 3.333e-03, 0.000e+00],
       [9.999e-01, 2.136e-03, 6.630e-03, 7.246e-03],
       [1.000e+00, 1.357e-03, 1.037e-03, 0.000e+00],
       [1.000e+00, 1.752e-03, 1.961e-03, 0.000e+00],
       [1.000e+00, 0.000e+00, 7.528e-03, 0.000e+00],
       [1.000e+00, 6.400e-04, 4.987e-04, 2.525e-03],
       [1.000e+00, 9.788e-04, 2.101e-03, 2.128e-03],
       [1.000e+00, 1.932e-03, 8.209e-05, 0.000e+00],
       [1.000e+00, 3.676e-03, 7.904e-04, 2.042e-03],
       [1.000e+00, 1.824e-03, 2.036e-03, 4.219e-03],
       [1.000e+00, 2.382e-03, 1.785e-03, 3.145e-03],
       [9.999e-01, 2.459e-03, 3.244e-03, 1.190e-02],
```

The preprocessing module provides the StandardScaler utility class, which is a quick and easy way to perform the following operation on an array-like dataset:

The standard score of a sample v is calculated as:

$$v_i' = (v_i - \mu_v)/\sigma_v$$

where μ_v is the mean of the training samples or zero if with_mean=False, and σ_v is the standard deviation of the training samples or one if with_std=False.

```
>>> from sklearn import preprocessing
>>> import numpy as np
>>> X_train = np.array([[ 1., -1.,  2.],
...                     [ 2.,  0.,  0.],
...                     [ 0.,  1., -1.]])
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> scaler
StandardScaler()

>>> scaler.mean_
array([1. ..., 0. ..., 0.33...])

>>> scaler.scale_
array([0.81..., 0.81..., 1.24...])

>>> X_scaled = scaler.transform(X_train)
>>> X_scaled
array([[ 0.  ..., -1.22...,  1.33...],
[ 1.22...,  0.  ..., -0.26...],
       [-1.22...,  1.22..., -1.06...]])
```

Scaled data has zero mean and unit variance:

```
>>> X_scaled.mean(axis=0) array([0.,
0., 0.])

>>> X_scaled.std(axis=0)
array([1., 1., 1.])
```

Data Splitting

In machine learning we usually split our data into two subsets: training data and testing data (and sometimes to three: train, validate and test), and fit our model on the train data, in order to make predictions on the test data. Training data and test data are two important concepts in machine learning.

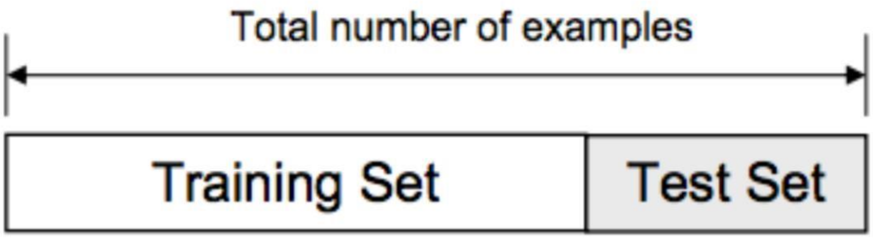
Training Data

The training set contains a known output and the model learns on this data in order to be generalized to other data later on. The observations in the training set form the experience that the algorithm uses to learn. In supervised learning problems, each observation consists of an observed output variable and one or more observed input variables.

Test Data

The test dataset (or subset) in order to test our model's prediction on this subset. The test set is a set of observations used to evaluate the performance of the model using some performance metric. It is important that no observations from the training set are included in the test set. If the test set does contain examples from the training set, it will be difficult to assess whether the algorithm has learned to generalize from the training set or has simply memorized it.

A program that generalizes well will be able to effectively perform a task with new data. In contrast, a program that memorizes the training data by learning an overly complex model could predict the values of the response variable for the training set accurately, but will fail to predict the value of the response variable for new examples. A program that memorizes its observations may not perform its task well, as it could memorize relations and structures that are noise or coincidence.



When the data is splitted, one of two thing might happen: we overfit the model or we underfit the model. We don't want any of these things to happen, because they affect the predictability of our model.

Student Exercise

Task 1

Thoroughly attempt and execute the notebooks provided with this lab. Submit the same notebooks as submission for this lab on LMS (BlackBoard).