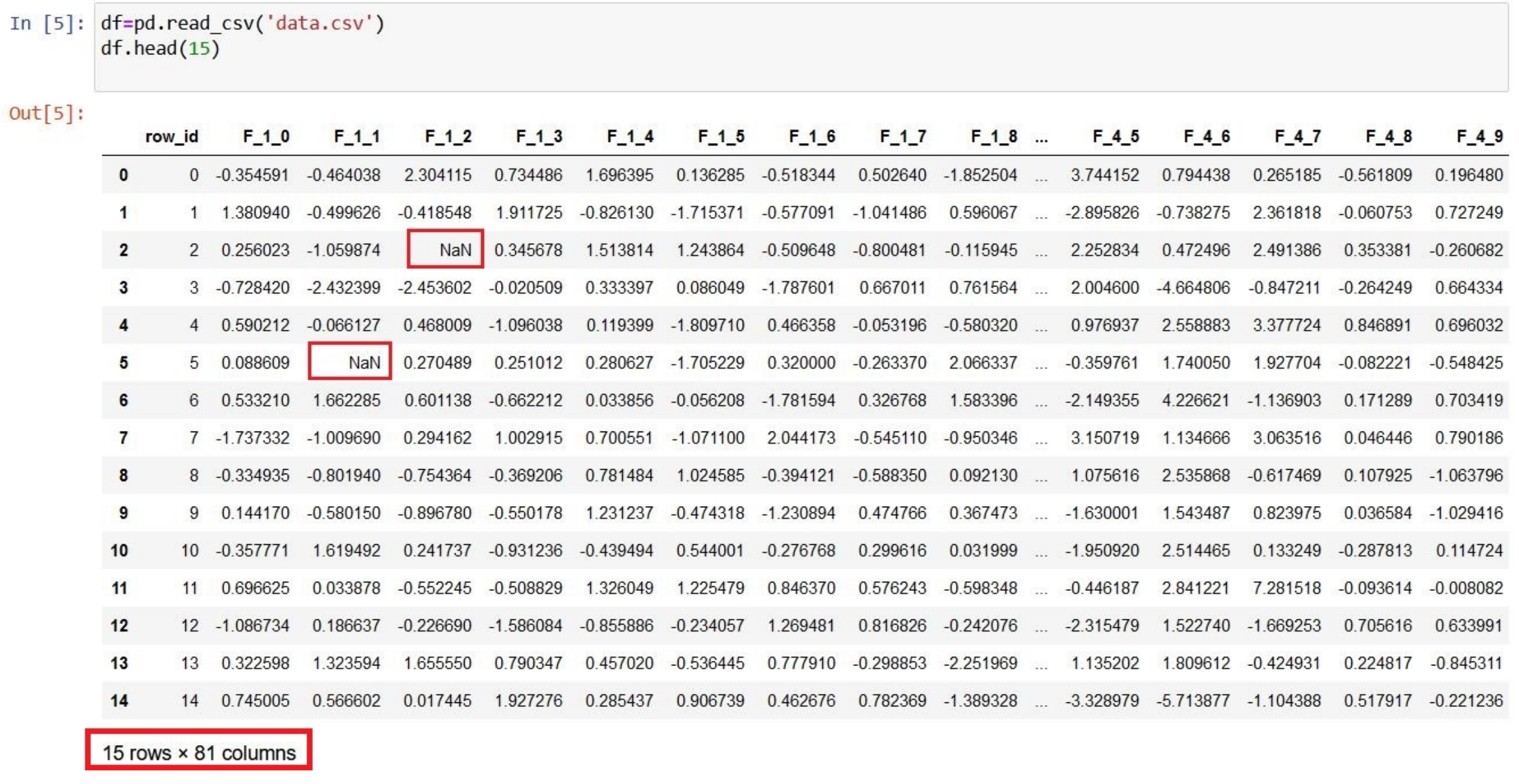
Dealing with Missing Values in Dataset

Mousa Tayseer Jafar

Deakin University, Australia

Introduction

What is a Missing Value? Missing data is defined as the values or data that is not stored (or not present)ăfor some variable/s in the given dataset. Missing value can bias the results of the machine learning models and/or reduce the accuracy of the model. Below is a sample of the missing data from the Tabular Playground Series - June 2022 dataset.

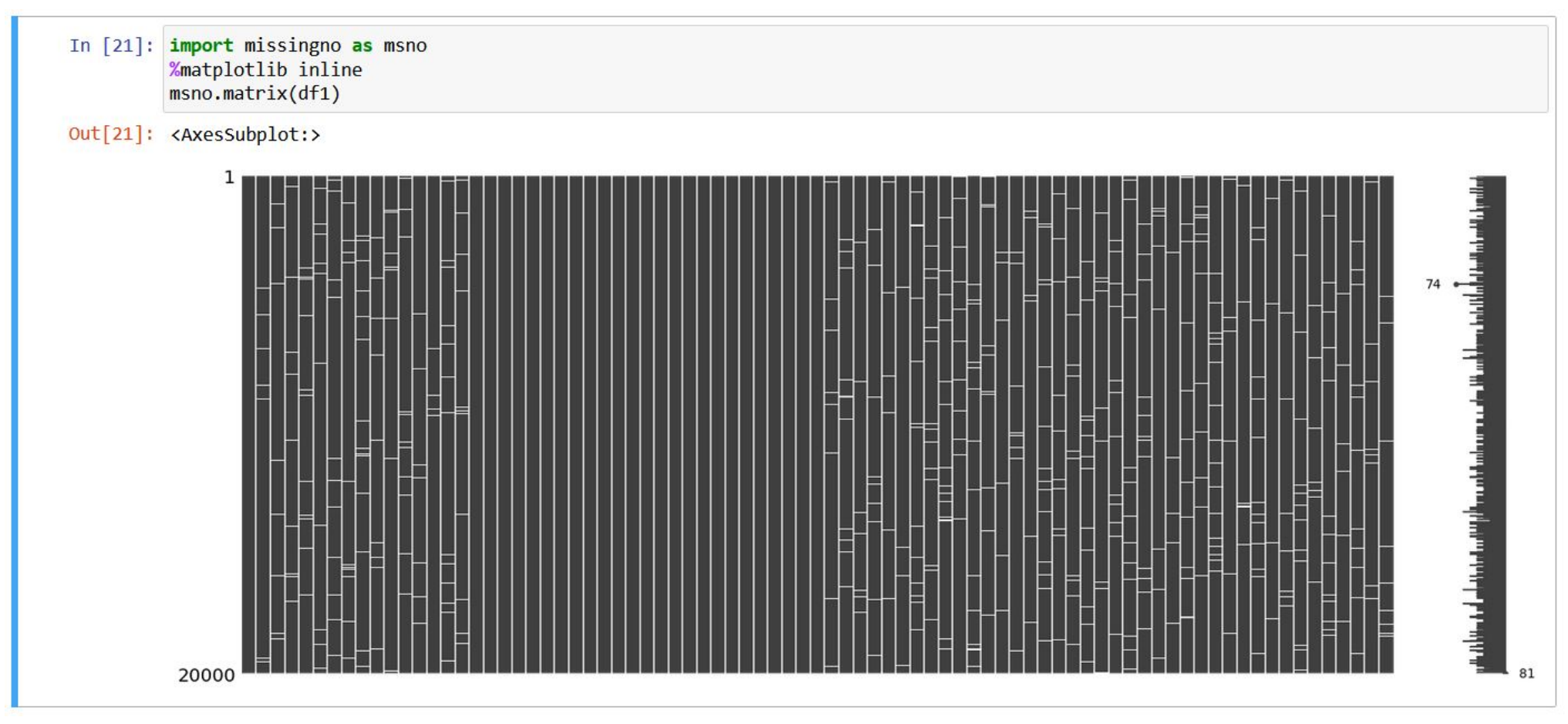


```
In [5]: df=pd.read_csv('data.csv')
        df.head(15)

Out[5]:
    row_id       F_1_0      F_1_1      F_1_2      F_1_3      F_1_4      F_1_5      F_1_6      F_1_7      F_1_8  ...      F_4_5      F_4_6      F_4_7      F_4_8      F_4_9
 0       0   -0.354591  -0.464038   2.304115   0.734486   1.696395   0.136285  -0.518344   0.502640  -1.852504  ...   3.744152   0.794438   0.265185  -0.561809   0.196480
 1       1    1.380940  -0.499626  -0.418548   1.911725  -0.826130  -1.715371  -0.577091  -1.041486   0.596067  ...  -2.895826  -0.738275   2.361818  -0.060753   0.727249
 2       2    0.256023  -1.059874        NaN   0.345678   1.513814   1.243864  -0.509648  -0.800481  -0.115945  ...   2.252834   0.472496   2.491386   0.353381  -0.260682
 3       3   -0.728420  -2.432399  -2.453602  -0.020509   0.333397   0.086049  -1.787601   0.667011   0.761564  ...   2.004600  -4.664806  -0.847211  -0.264249   0.664334
 4       4    0.590212  -0.066127   0.468009  -1.096038   0.119399  -1.809710   0.466358  -0.053196  -0.580320  ...   0.976937   2.558883   3.377724   0.846891   0.696032
 5       5    0.088609        NaN   0.270489   0.251012   0.280627  -1.705229   0.320000  -0.263370   2.066337  ...  -0.359761   1.740050   1.927704  -0.082221  -0.548425
 6       6    0.533210   1.662285   0.601138  -0.662212   0.033856  -0.056208  -1.781594   0.326768   1.583396  ...  -2.149355   4.226621  -1.136903   0.171289   0.703419
 7       7   -1.737332  -1.009690   0.294162   1.002915   0.700551  -1.071100   2.044173  -0.545110  -0.950346  ...   3.150719   1.134666   3.063516   0.046446   0.790186
 8       8   -0.334935  -0.801940  -0.754364  -0.369206   0.781484   1.024585  -0.394121  -0.588350   0.092130  ...   1.075616   2.535868  -0.617469   0.107925  -1.063796
 9       9    0.144170  -0.580150  -0.896780  -0.550178   1.231237  -0.474318  -1.230894   0.474766   0.367473  ...  -1.630001   1.543487   0.823975   0.036584  -1.029416
10      10   -0.357771   1.619492   0.241737  -0.931236  -0.439494   0.544001  -0.276768   0.299616   0.031999  ...  -1.950920   2.514465   0.133249  -0.287813   0.114724
11      11    0.696625   0.033878  -0.552245  -0.508829   1.326049   1.225479   0.846370   0.576243  -0.598348  ...  -0.446187   2.841221   7.281518  -0.093614  -0.008082
12      12   -1.086734   0.186637  -0.226690  -1.586084  -0.855886  -0.234057   1.269481   0.816826  -0.242076  ...  -2.315479   1.522740  -1.669253   0.705616   0.633991
13      13    0.322598   1.323594   1.655550   0.790347   0.457020  -0.536445   0.777910  -0.298853  -2.251969  ...   1.135202   1.809612  -0.424931   0.224817  -0.845311
14      14    0.745005   0.566602   0.017445   1.927276   0.285437   0.906739   0.462676   0.782369  -1.389328  ...  -3.328979  -5.713877  -1.104388   0.517917  -0.221236

15 rows × 81 columns
```

Visualization Missing Values

How is Missing Value Represented In The Dataset? In Pandas, usually, missing values are represented by NaN.

- The real-world data often has a lot of missing values.
- The cause of missing values can be data corruption or failure to record data.
- The handling of missing data is very important during the preprocessing of the dataset as many machine learning algorithms do not support missing values.
- Three problems associated with missing values:
  - Loss of efficiency,
  - Complications in handling and analyzing the data,
  - Bias resulting from differences between missing and complete data.

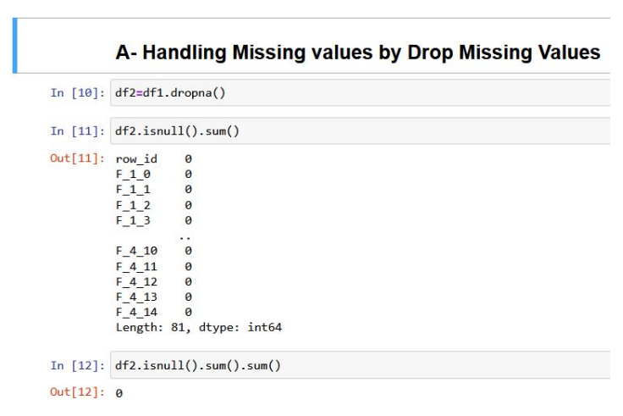


```
In [21]: import missingno as msno
         %matplotlib inline
         msno.matrix(df1)

Out[21]: <AxesSubplot:>
```

Data Preprocessing

How To Handle Missing Values? Analyze each column with missing values carefully to understand the reasons behind the missing values, as it is crucial to find out the strategy for handling the missing values. There are many ways of handling missing values We propose the below methods to handle the missing values:

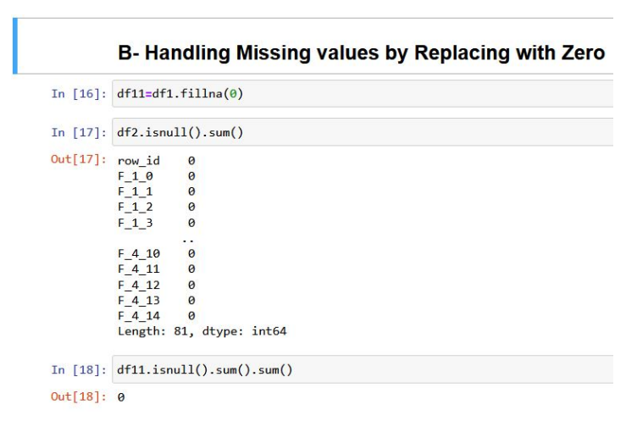
- Deleting the Missing values
- Replacing With Arbitrary Value (Zero)
- Replacing with Previous Value Forward Fill
- Replacing with Next Value Backward Fill
- Interpolation Method



A- Handling Missing values by Drop Missing Values

```
In [10]: df2=df1.dropna()

In [11]: df2.isnull().sum()

Out[11]: row_id    0
         F_1_0     0
         F_1_1     0
         F_1_2     0
         F_1_3     0
                  ..
         F_4_10    0
         F_4_11    0
         F_4_12    0
         F_4_13    0
         F_4_14    0
         Length: 81, dtype: int64

In [12]: df2.isnull().sum().sum()

Out[12]: 0
```

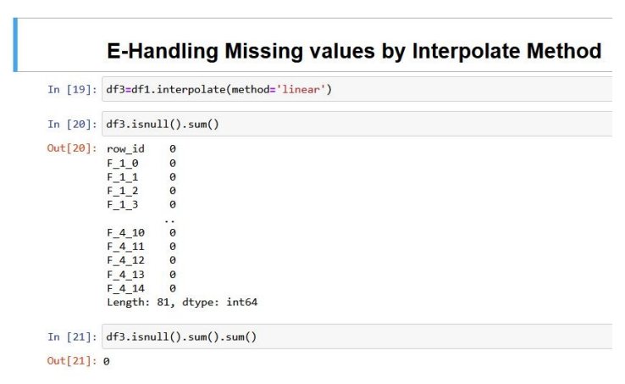
Deleting Missing values



B- Handling Missing values by Replacing with Zero

```
In [16]: df11=df1.fillna(0)

In [17]: df2.isnull().sum()

Out[17]: row_id    0
         F_1_0     0
         F_1_1     0
         F_1_2     0
         F_1_3     0
                  ..
         F_4_10    0
         F_4_11    0
         F_4_12    0
         F_4_13    0
         F_4_14    0
         Length: 81, dtype: int64

In [18]: df11.isnull().sum().sum()

Out[18]: 0
```

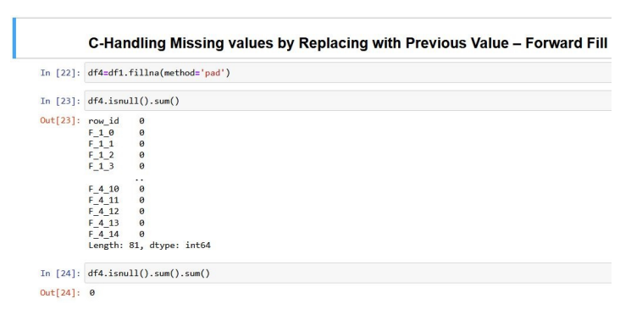
Replacing with Zero



E-Handling Missing values by Interpolate Method

```
In [19]: df3=df1.interpolate(method='linear')

In [20]: df3.isnull().sum()

Out[20]: row_id    0
         F_1_0     0
         F_1_1     0
         F_1_2     0
         F_1_3     0
                  ..
         F_4_10    0
         F_4_11    0
         F_4_12    0
         F_4_13    0
         F_4_14    0
         Length: 81, dtype: int64

In [21]: df3.isnull().sum().sum()

Out[21]: 0
```

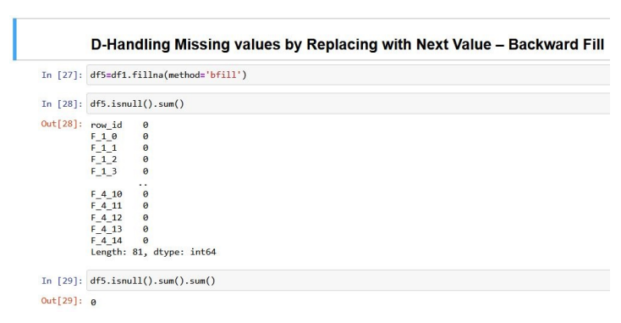
Replacing with linear



C-Handling Missing values by Replacing with Previous Value – Forward Fill

```
In [22]: df4=df1.fillna(method='pad')

In [23]: df4.isnull().sum()

Out[23]: row_id    0
         F_1_0     0
         F_1_1     0
         F_1_2     0
         F_1_3     0
                  ..
         F_4_10    0
         F_4_11    0
         F_4_12    0
         F_4_13    0
         F_4_14    0
         Length: 81, dtype: int64

In [24]: df4.isnull().sum().sum()

Out[24]: 0
```

Forward fill



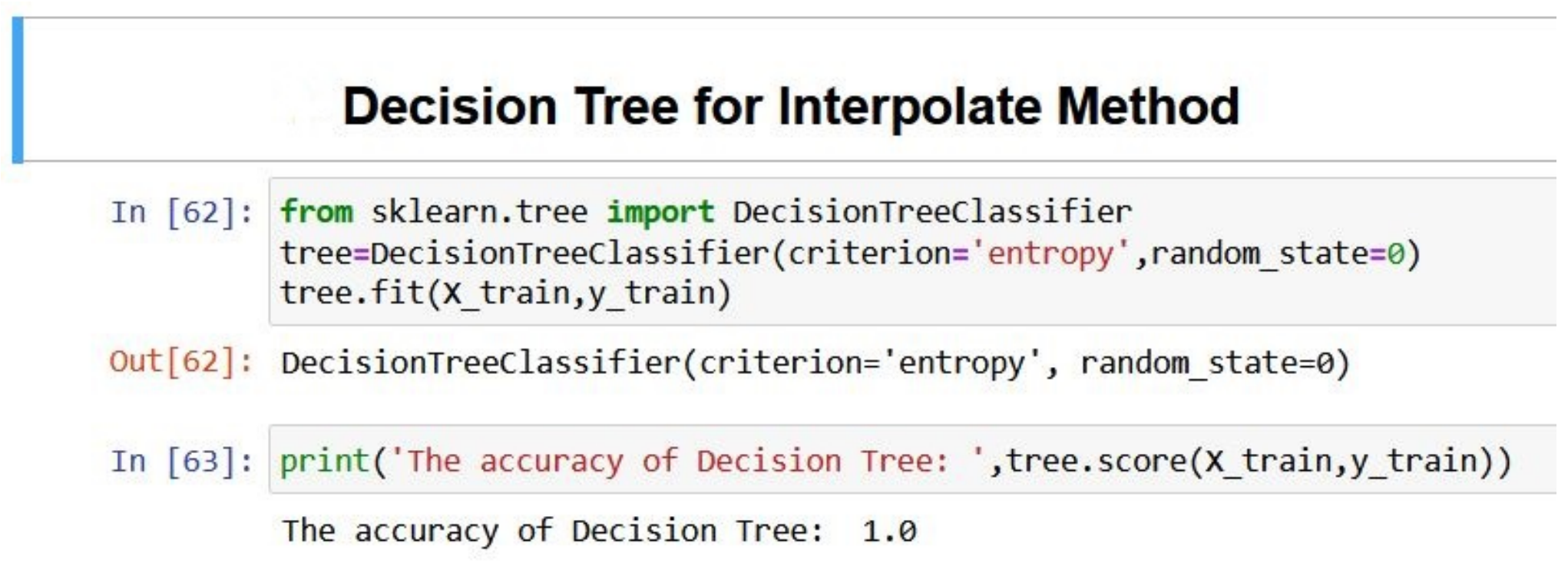
D-Handling Missing values by Replacing with Next Value – Backward Fill

```
In [27]: df5=df1.fillna(method='bfill')

In [28]: df5.isnull().sum()

Out[28]: row_id    0
         F_1_0     0
         F_1_1     0
         F_1_2     0
         F_1_3     0
                  ..
         F_4_10    0
         F_4_11    0
         F_4_12    0
         F_4_13    0
         F_4_14    0
         Length: 81, dtype: int64

In [29]: df5.isnull().sum().sum()

Out[29]: 0
```

Backward Fill

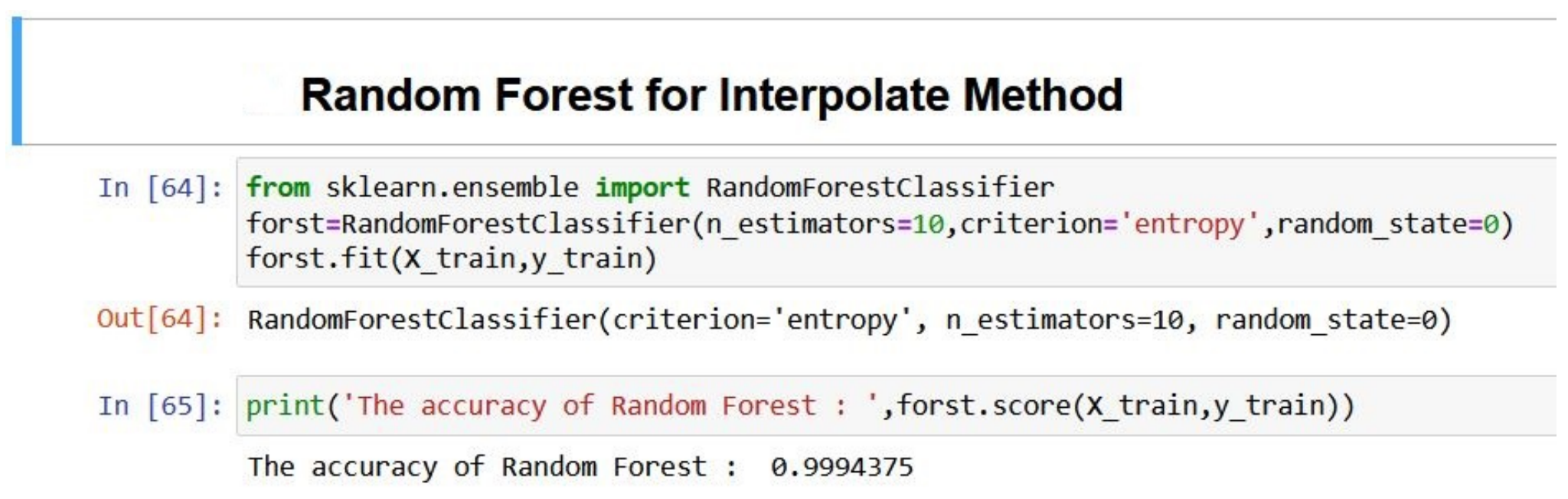
Applying Machine Learning Models

Missing data is a common problem in statistical analysis. In this work, we have been applying three Machine Learning Algorithms to measure accuracy after handling the missing values **Decision Tree, Random Forest, and Linear Regression.**



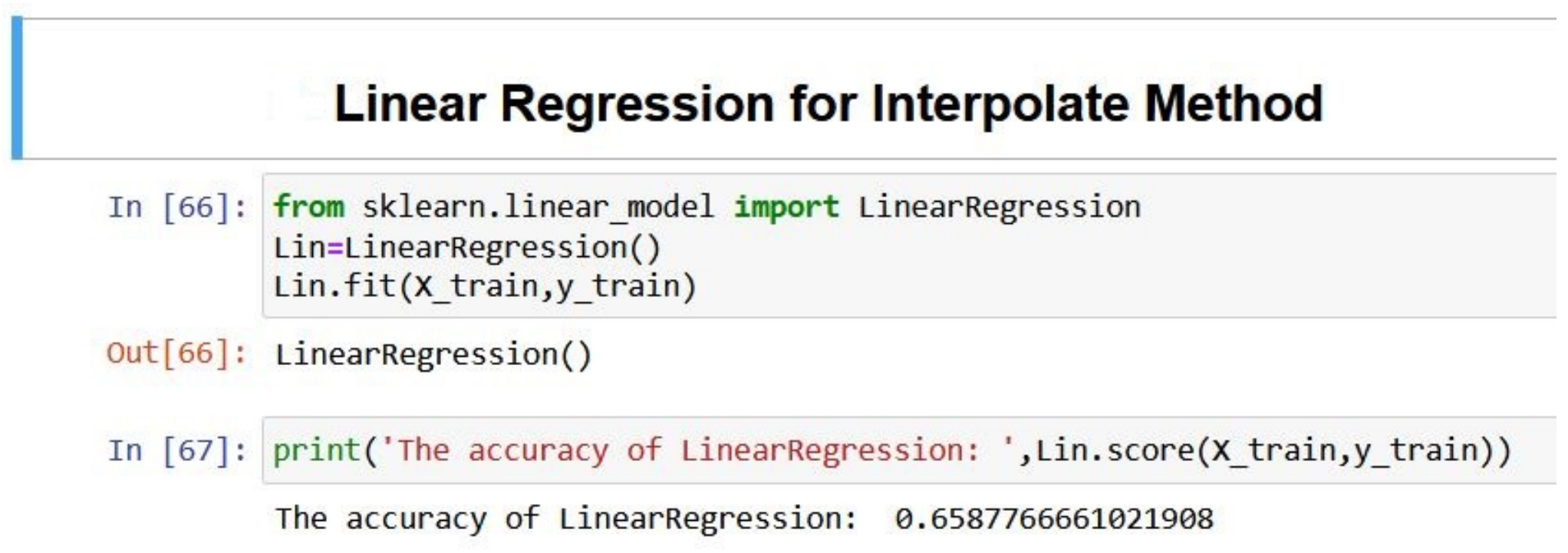
Decision Tree for Interpolate Method

```
In [62]: from sklearn.tree import DecisionTreeClassifier
         tree=DecisionTreeClassifier(criterion='entropy',random_state=0)
         tree.fit(X_train,y_train)

Out[62]: DecisionTreeClassifier(criterion='entropy', random_state=0)

In [63]: print('The accuracy of Decision Tree: ',tree.score(X_train,y_train))

         The accuracy of Decision Tree:  1.0
```



Random Forest for Interpolate Method

```
In [64]: from sklearn.ensemble import RandomForestClassifier
         forst=RandomForestClassifier(n_estimators=10,criterion='entropy',random_state=0)
         forst.fit(X_train,y_train)

Out[64]: RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)

In [65]: print('The accuracy of Random Forest : ',forst.score(X_train,y_train))

         The accuracy of Random Forest :  0.9994375
```



Linear Regression for Interpolate Method

```
In [66]: from sklearn.linear_model import LinearRegression
         Lin=LinearRegression()
         Lin.fit(X_train,y_train)

Out[66]: LinearRegression()

In [67]: print('The accuracy of LinearRegression: ',Lin.score(X_train,y_train))

         The accuracy of LinearRegression:  0.6587766661021908
```

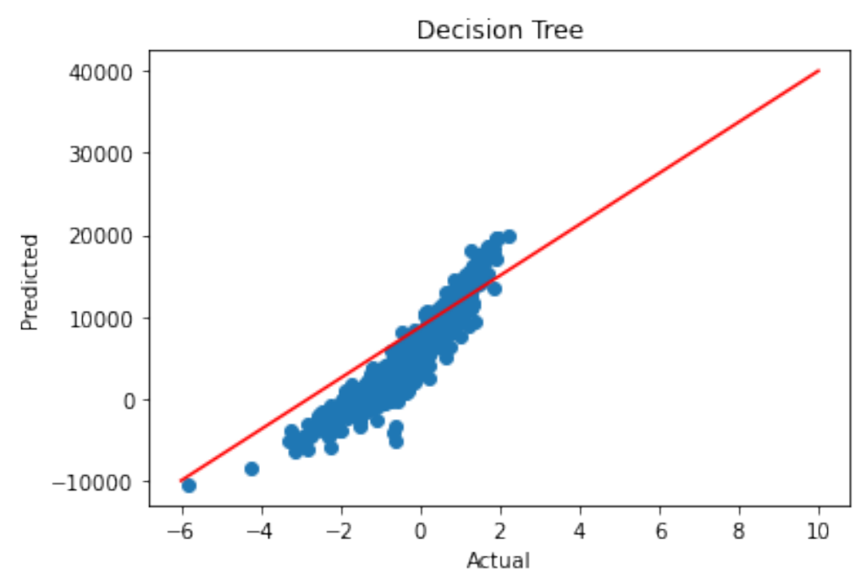
Experiment

Missing data is a common problem in statistical analysis.

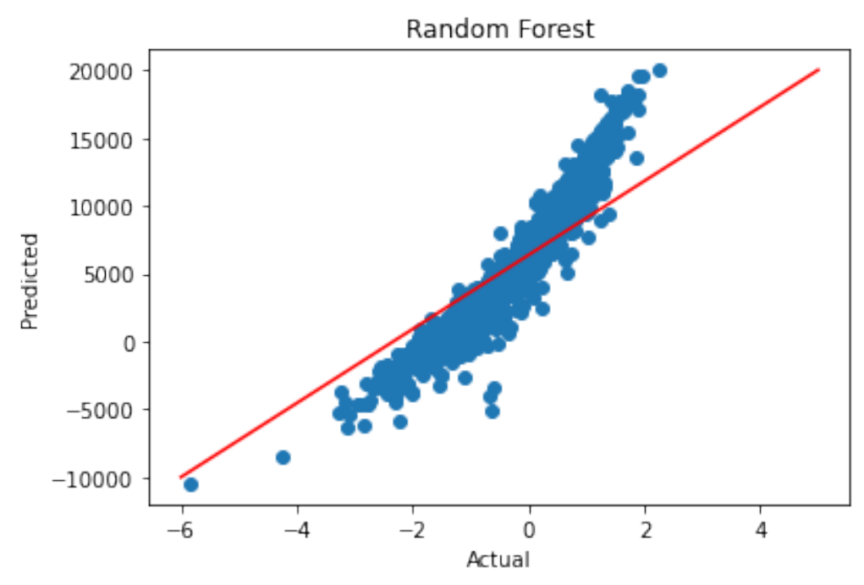
Random Forest, Decision Tree, and Linear Regression, were used as Machine Learning Methods to measure the Accuracy after handling the missing values. Accuracy is generated using the number of correct predictions on the test dataset to find the actual class label against the predicted class label for each category. The accuracy represents the total correct prediction overall the total prediction, as shown in equation 1.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

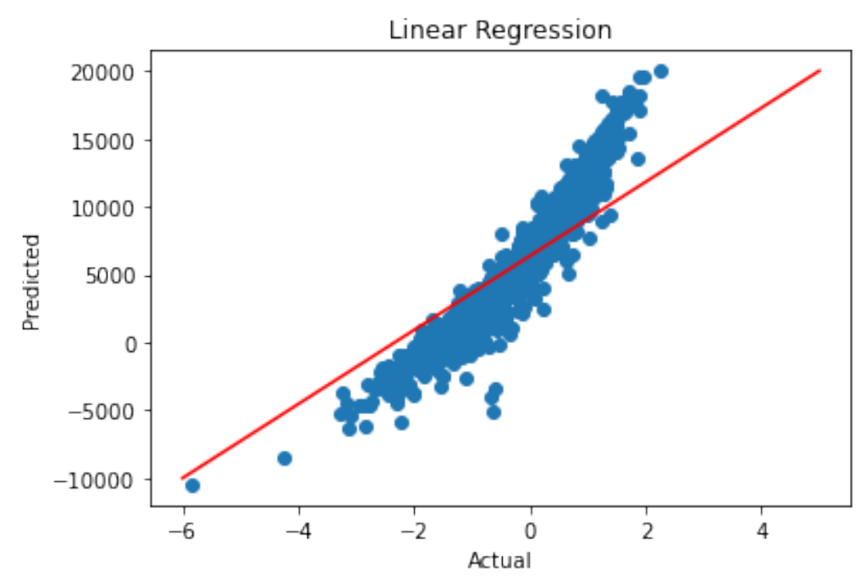
Handling Missing Values	Decision Tree	Random Forest	Linear Regression
Drop Missing Values	1.0	0.9994858	0.9047421
Missing Values Zero	1.0	0.9993125	0.7113801
Interpolate Method	1.0	0.9994375	0.6587766
Forward Fill	1.0	0.9993125	0.6336116
Backward Fill	1.0	0.9993125	0.6207112



Predicted result for the DT



Predicted result for the RF



Predicted result for the LR

Conclusion

This work has introduced an approach for identifying and handling the missing values in the dataset. Several experiments have been conducted with three ML algorithms (DT, RF, and LR) to evaluate the efficiency and the performance of thes approaches. All tests are experimented based on the Tabular Playgro June 2022 dataset. Experiments have shown that the Decis be affected by handling missing values where th equals 100

Acknowledgement

- FLIP00 team