practical2

May 4, 2024

[1]:
```
# Data Wrangling II
# Create an "Academic performance" dataset of students and perform the␣
↪following operations using
# Python.
#   1. Scan all variables for missing values and inconsistencies. If there are␣
↪missing values and/or
#      inconsistencies, use any of the suitable techniques to deal with them.
#   2. Scan all numeric variables for outliers. If there are outliers, use any␣
↪of the suitable techniques
#      to deal with them.
#   3. Apply data transformations on at least one of the variables. The purpose␣
↪of this
#      transformation should be one of the following reasons: to change the␣
↪scale for better
#      understanding of the variable, to convert a non-linear relation into a␣
↪linear one, or to decrease
#      the skewness and convert the distribution into a normal distribution.
```

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import StandardScaler
```

[3]:
```
data = pd.read_csv('../academic performance.csv')
data.head()
```

[3]:
```
  gender NationalITy PlaceofBirth     StageID GradeID SectionID Topic  \
0      M          KW       KuwaIT  lowerlevel    G-04         A    IT
1      M          KW       KuwaIT  lowerlevel    G-04         A    IT
2      M          KW       KuwaIT  lowerlevel    G-04         A    IT
3      M          KW       KuwaIT  lowerlevel    G-04         A    IT
4      M          KW       KuwaIT  lowerlevel    G-04         A    IT

  Semester Relation  raisedhands  VisITedResources  AnnouncementsView  \
```

```
0        F   Father       15.0               16                 2
1        F   Father       20.0               20                 3
2        F   Father       10.0                7                 0
3        F   Father       30.0               25                 5
4        F   Father       40.0               50                12

   Discussion ParentAnsweringSurvey ParentschoolSatisfaction  \
0          20                   Yes                     Good
1          25                   Yes                     Good
2          30                    No                      Bad
3          35                    No                      Bad
4          50                    No                      Bad

  StudentAbsenceDays Class
0            Under-7     M
1            Under-7     M
2            Above-7     L
3            Above-7     L
4            Above-7     M
```

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 480 entries, 0 to 479
Data columns (total 17 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   gender                    480 non-null    object
 1   NationalITy               480 non-null    object
 2   PlaceofBirth              480 non-null    object
 3   StageID                   480 non-null    object
 4   GradeID                   480 non-null    object
 5   SectionID                 480 non-null    object
 6   Topic                     480 non-null    object
 7   Semester                  480 non-null    object
 8   Relation                  480 non-null    object
 9   raisedhands               455 non-null    float64
 10  VisITedResources          480 non-null    int64
 11  AnnouncementsView         480 non-null    int64
 12  Discussion                480 non-null    int64
 13  ParentAnsweringSurvey     480 non-null    object
 14  ParentschoolSatisfaction  480 non-null    object
 15  StudentAbsenceDays        480 non-null    object
 16  Class                     480 non-null    object
dtypes: float64(1), int64(3), object(13)
memory usage: 63.9+ KB
```

[5]:
```
#   1. Scan all variables for missing values and inconsistencies. If there are␣
↪missing values and/or
#      inconsistencies, use any of the suitable techniques to deal with them.
data.isnull().sum() #check for missing values
```

[5]:
```
gender                      0
NationalITy                 0
PlaceofBirth                0
StageID                     0
GradeID                     0
SectionID                   0
Topic                       0
Semester                    0
Relation                    0
raisedhands                25
VisITedResources            0
AnnouncementsView           0
Discussion                  0
ParentAnsweringSurvey       0
ParentschoolSatisfaction    0
StudentAbsenceDays          0
Class                       0
dtype: int64
```

[6]:
```
# we can remove null values by dropping rows or fill null values as per features
# data1 = data.interpolate()
```

[7]:
```
# data1.isnull().sum()
```

[8]:
```
mean_val = data['raisedhands'].mean()
data['raisehands']=data['raisehands'].fillna(mean_val)
data2.isnull().sum()
```

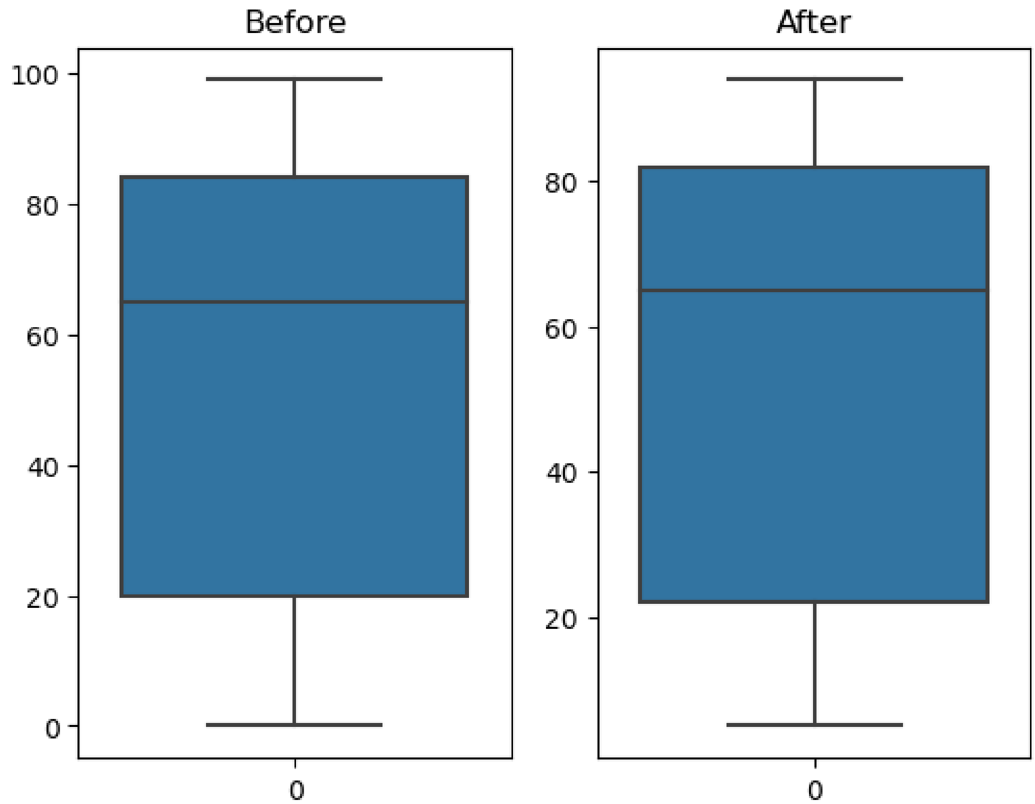
[8]:
```
gender                     0
NationalITy                0
PlaceofBirth               0
StageID                    0
GradeID                    0
SectionID                  0
Topic                      0
Semester                   0
Relation                   0
raisedhands                0
VisITedResources           0
AnnouncementsView          0
Discussion                 0
ParentAnsweringSurvey      0
```

```
ParentschoolSatisfaction    0
StudentAbsenceDays          0
Class                       0
dtype: int64
```

[9]:
```
# Or we can drop null value rows
# data.dropna(axis=0, inplace=True)
```

[10]:
```
#   2. Scan all numeric variables for outliers. If there are outliers, use any␣
 ↪of the suitable techniques
#       to deal with them.
fig,axis = plt.subplots(1, 2)
max_val = data2.VisITedResources.quantile(0.95)
min_val = data2.VisITedResources.quantile(0.05)
print("Before Shape", data.shape)
df = data2[(data2['VisITedResources'] > min_val) & (data2['VisITedResources'] <␣
 ↪max_val)]
print("After Shape", df.shape)
sns.boxplot(data2['VisITedResources'], orient='v', ax=axis[0])
axis[0].title.set_text('Before')
sns.boxplot(df['VisITedResources'], orient='v', ax=axis[1])
axis[1].title.set_text('After')
plt.show()
```

```
Before Shape (480, 17)
After Shape (427, 17)
```

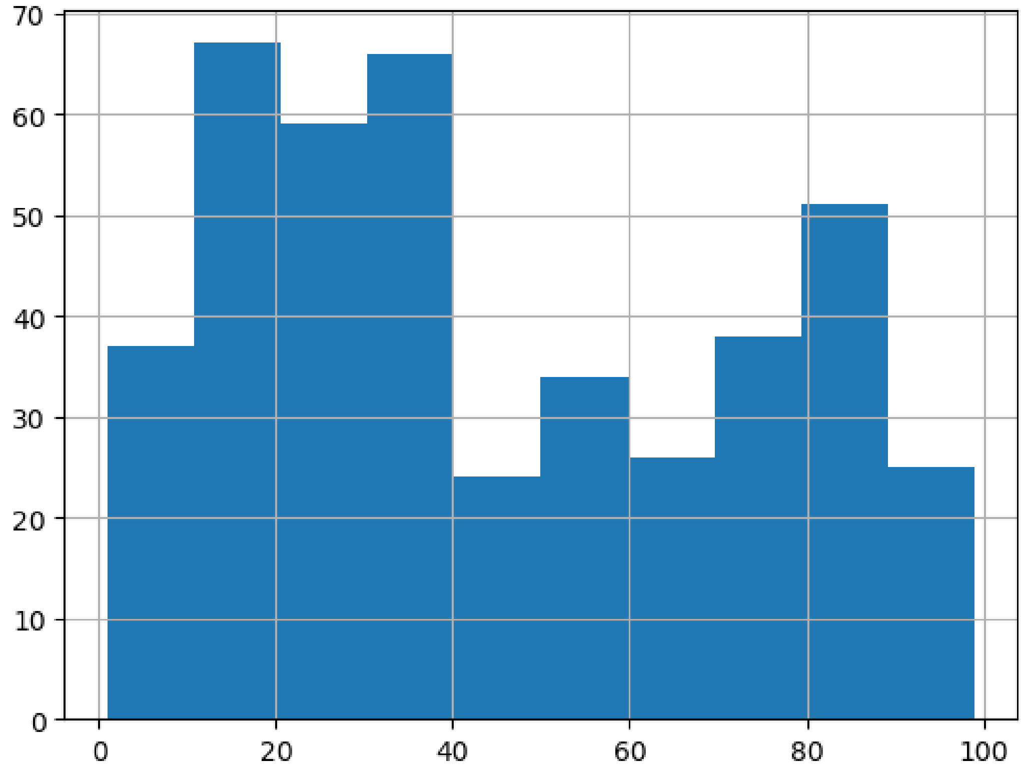


[11]:
```
#   3. Apply data transformations on at least one of the variables. The purpose␣
↪of this
#       transformation should be one of the following reasons: to change the␣
↪scale for better
#       understanding of the variable, to convert a non-linear relation into a␣
↪linear one, or to decrease
#       the skewness and convert the distribution into a normal distribution.
```

[12]:
```
scaler = StandardScaler()
x = df[['raisedhands', 'VisITedResources', 'AnnouncementsView', 'Discussion']]
scaledf = scaler.fit_transform(x)
print(scaledf)
```

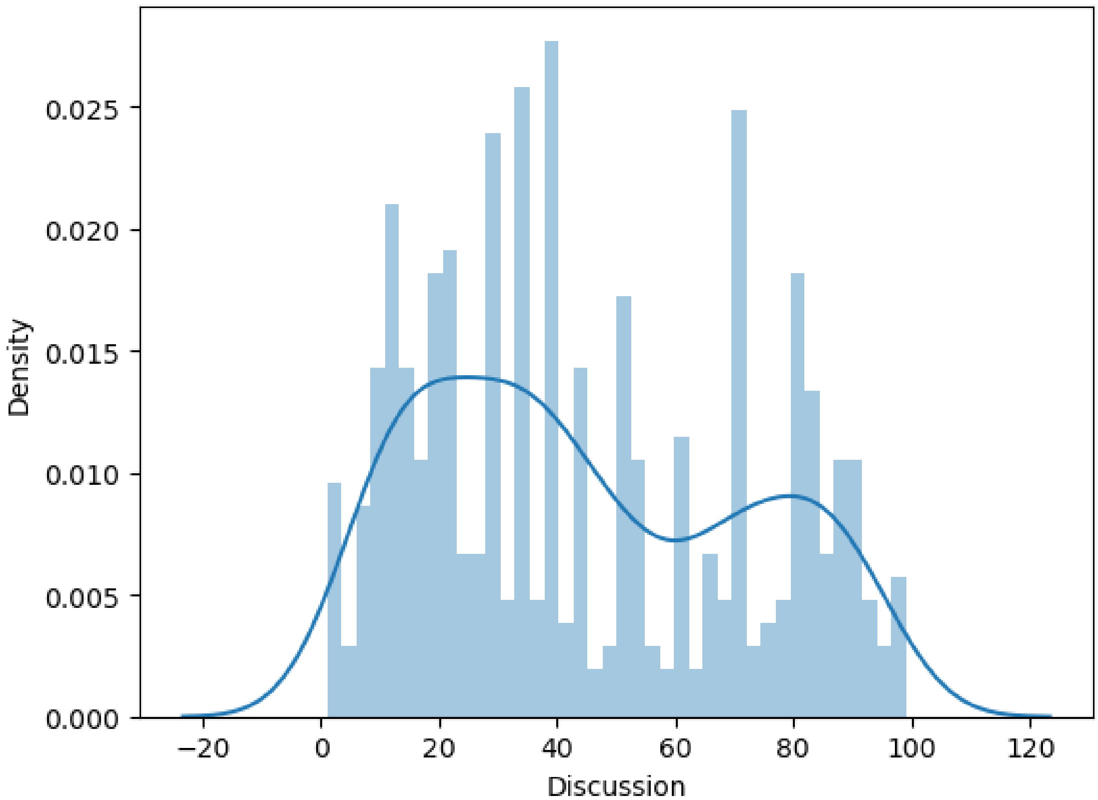
```
[[-1.15922617 -1.29844429 -1.42428794 -0.90164582]
 [-0.99010159 -1.16788899 -1.38643105 -0.71803137]
 [-1.32835075 -1.59219371 -1.50000172 -0.53441693]
 …
 [ 0.19377045  0.59460753 -0.55357945 -0.57113982]
 [-0.65185244 -1.26580546 -0.97000525  0.45710106]
 [-0.48272786 -1.36372194 -0.62929323  0.6407155 ]]
```

[13]:
```
df.Discussion.hist()
plt.show()
```



[14]:
```
import scipy.stats as stats
```

[15]:
```
sns.distplot(df['Discussion'], bins = 40)
plt.show()
```



[16]:
```
# Checking the skewness
df['Discussion'].skew()
```

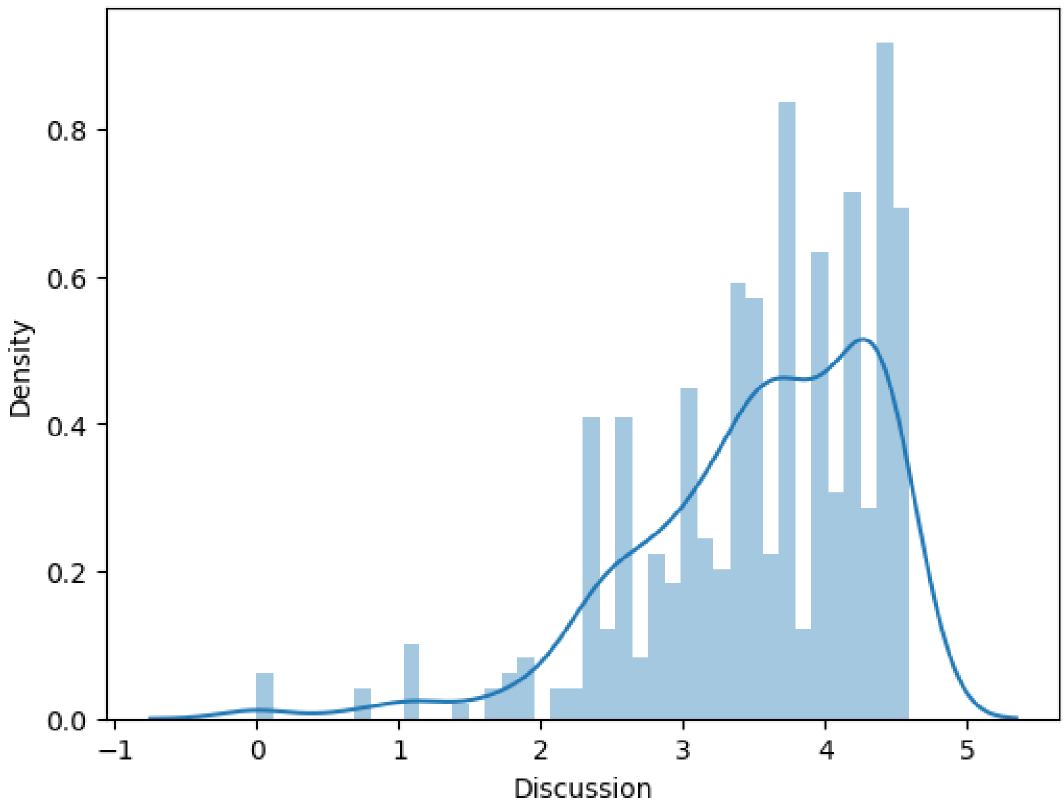
[16]: 0.33203952447202845

[17]:
```
# If you want to reduce skewness there are 4 methods, one of them is log
log = np.log(df['Discussion'])
print(log.skew())
```

-1.1910468123704019

[18]:
```
sns.distplot(log, bins = 40)
```

[18]: <Axes: xlabel='Discussion', ylabel='Density'>



0.8
0.6
0.4
0.2
0.0
Density
−1
0
1
2
3
4
5
Discussion