Batch: HO-ML 1 **Experiment Number: 01**

Roll Number: 16010422234 **Name: Chandana Galgali**

Aim of the Experiment: Data pre-processing by applying data normalization and data discretization

---

Program/ Steps:

1. Identify attribute suitable for normalization and discretization
2. Apply Z- score normalization on your dataset.
3. Apply discretization using Binning technique

Output/Result:

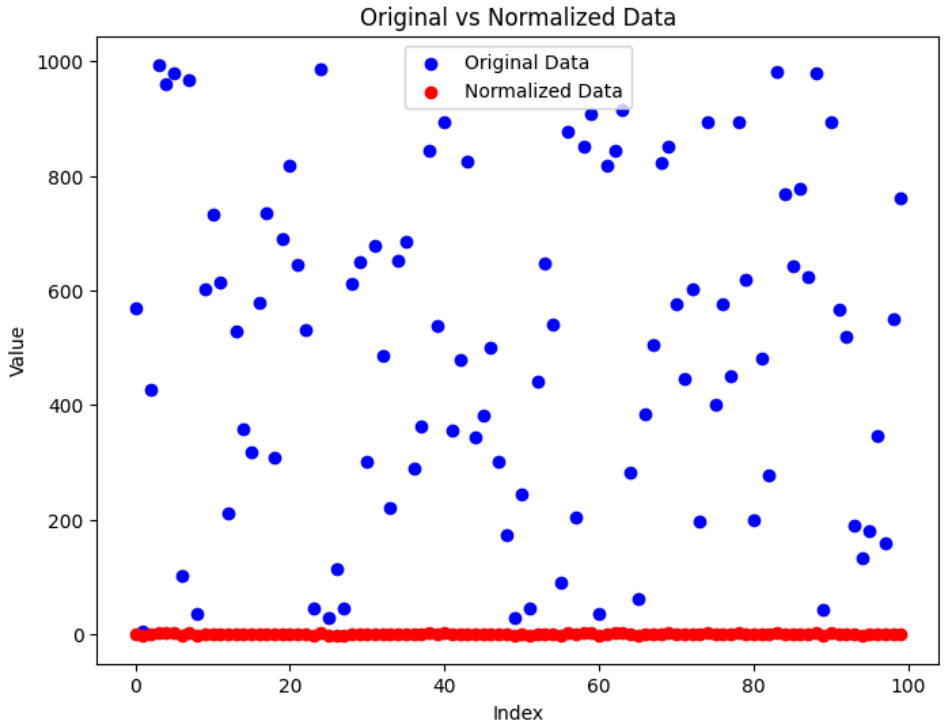
```
import random

import numpy as np

import matplotlib.pyplot as plt

data = [random.randint(0, 1000) for _ in range(100)]

mean = np.mean(data)

std = np.std(data)

normalized_data = [(x - mean) / std for x in data]

print("Original Value | Normalized Value")

print("---------------|-----------------")

for original, normalized in zip(data, normalized_data):

  print(f"{original:<15} | {normalized:.2f}")

plt.figure(figsize=(8, 6))

plt.scatter(range(len(data)), data, color='blue', label='Original Data')

plt.scatter(range(len(normalized_data)),   normalized_data,   color='red',
label='Normalized Data')
```

```
plt.xlabel('Index')

plt.ylabel('Value')

plt.title('Original vs Normalized Data')

plt.legend()

plt.show()
```

Original Value	Normalized Value
569	0.22
4	-1.74
426	-0.28
994	1.69
960	1.57
979	1.64
101	-1.40
968	1.60
36	-1.62
601	0.33
733	0.78
614	0.37
211	-1.02
529	0.08
357	-0.52
317	-0.65
578	0.25
736	0.80
308	-0.68
691	0.64
817	1.08
644	0.48
531	0.09
44	-1.60
986	1.66
29	-1.65
113	-1.36
45	-1.59
612	0.37
649	0.49
300	-0.71
677	0.59
486	-0.07
221	-0.99
651	0.50

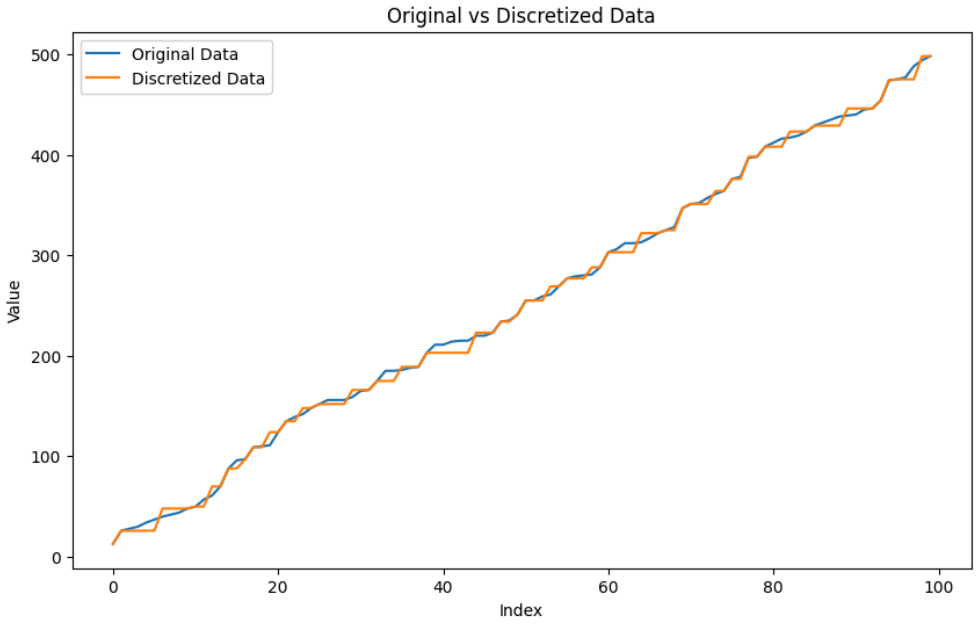
684	0.62
290	-0.75
362	-0.50
844	1.17
537	0.11
893	1.34
356	-0.52
479	-0.09
826	1.11
344	-0.56
382	-0.43
501	-0.02
300	-0.71
172	-1.15
29	-1.65
245	-0.90
46	-1.59
440	-0.23
647	0.49
540	0.12
89	-1.44
877	1.28
205	-1.04
851	1.19
907	1.39
35	-1.63
819	1.08
843	1.17
914	1.41
283	-0.77
61	-1.54
385	-0.42
505	-0.00
822	1.09
851	1.19
577	0.25
445	-0.21
602	0.33
196	-1.07
894	1.34
400	-0.37
575	0.24
451	-0.19
894	1.34
618	0.39
200	-1.06
481	-0.09

```
277             | -0.79
982             | 1.65
767             | 0.90
643             | 0.47
778             | 0.94
623             | 0.40
978             | 1.63
42              | -1.60
894             | 1.34
567             | 0.21
519             | 0.04
189             | -1.10
132             | -1.29
180             | -1.13
347             | -0.55
158             | -1.20
551             | 0.16
760             | 0.88
```



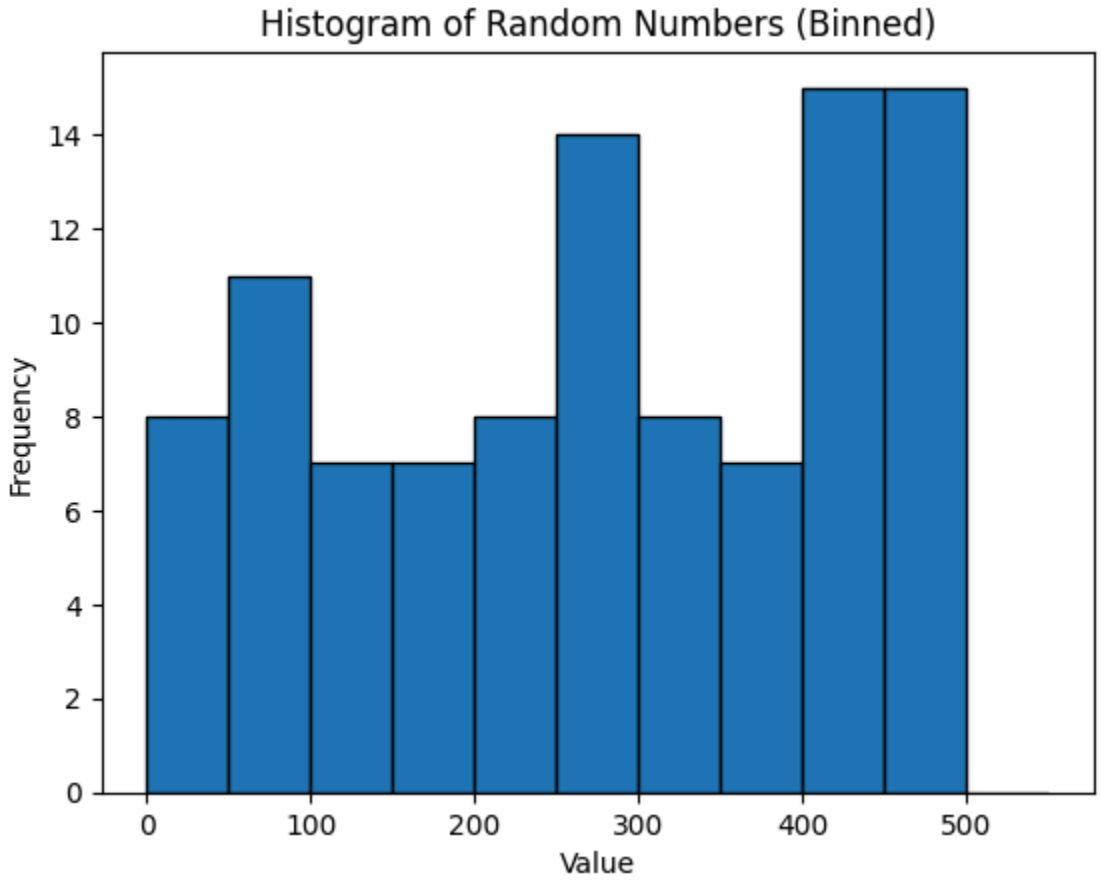

```python
import random
import numpy as np
import matplotlib.pyplot as plt
data = [random.randint(0, 500) for _ in range(100)]
data.sort()
discretized_data = []
for i in range(0, 501, 25):
```

```
  group = [x for x in data if i <= x < i + 25]
  if group:
    low = min(group)
    high = max(group)
    percentile_50 = np.percentile(group, 50)
    for x in group:
      discretized_data.append(low if x <= percentile_50 else high)

plt.figure(figsize=(10, 6))
plt.plot(data, label='Original Data')
plt.plot(discretized_data, label='Discretized Data')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Original vs Discretized Data')
plt.legend()
plt.show()
```




```
import random
import matplotlib.pyplot as plt

data = [random.randint(0, 500) for _ in range(100)]

bin_edges = range(0, 551, 50)  # Bins: 0-50, 51-100, ..., 451-500

plt.hist(data, bins=bin_edges, edgecolor='black')
plt.xlabel('Value')
```

```
plt.ylabel('Frequency')
plt.title('Histogram of Random Numbers (Binned)')
plt.show()
```



Post Lab Question-Answers:

Explain with example Min-Max normalization technique.

Ans: Min-Max Normalization is a data normalization technique used to scale data values to a fixed range, typically [0, 1]. This technique ensures that all attributes contribute equally to the analysis by transforming the data values into a uniform scale.

Formula: $v' = \frac{v - \min(A)}{\max(A) - \min(A)}$

where:

- v is the original value.
- min(A) is the minimum value of attribute AAA.
- max(A) is the maximum value of attribute AAA.

- v′ is the normalized value.

Example: Suppose we have an attribute "Height" with values ranging from 150 cm to 200 cm. To normalize a value of 180 cm:

1. Determine the Min and Max Values:
    - Min = 150 cm
    - Max = 200 cm
2. Apply the Min-Max Formula:

$$v' = \frac{180 - 150}{200 - 150} = \frac{30}{50} = 0.6$$

Thus, the normalized value of 180 cm is 0.6, which falls within the [0, 1] range.

This normalization method is straightforward and effective for scaling data when the minimum and maximum values are known and when it is crucial to maintain the data within a specific range for uniformity in analysis.

Outcomes: Comprehend basics of machine learning

Conclusion (based on the Results and outcomes achieved):
In this experiment, applying z-score normalization and binning for discretization effectively improved data quality and mining efficiency. Normalization ensured uniformity across attributes, while discretization simplified continuous data into manageable intervals. These pre-processing techniques enhanced the accuracy and computational efficiency of subsequent data mining tasks.

References:

Books/ Journals/ Websites:

1. Han, Kamber, "Data Mining Concepts and Techniques", Morgan Kaufmann 3nd Edition