cfhekhtxa

April 29, 2024

[ ]:
```
#Standarisation using the titanic dataset
#z index based scaling
import numpy as np
import pandas as pd
import os
# for dirname, _, filenames in os.walk('/kaggle/input/titanicdataset-traincsv'):
#     for filename in filenames:
#         print(os.path.join(dirname, filename))
df = pd.read_csv('/content/train.csv', usecols=['Pclass', 'Age', 'Fare',␣
↪'Survived'])
df.head()
```

[ ]:

	Survived	Pclass	Age	Fare
0	0	3	22.0	7.2500
1	1	1	38.0	71.2833
2	1	3	26.0	7.9250
3	1	1	35.0	53.1000
4	0	3	35.0	8.0500

1. Standardization / Z-Score Where all features and variables are brought to a similar scale. By centering the variables at zero.

Formula: z = (x - (x_mean))/std

This is done through

[ ]:
```
df.isnull().sum()
```

[ ]:
```
Survived      0
Pclass        0
Age         177
Fare          0
dtype: int64
```

[ ]:
```
#Performing standardization
#Using StandardScaler from Scikit-Learn

from sklearn.preprocessing import StandardScaler
scalar = StandardScaler()
```

[ ]:
```
df_scaled = scalar.fit_transform(df)
df_scaled
```

[ ]:
```
array([[-0.78927234,  0.82737724, -0.53037664, -0.50244517],
       [ 1.2669898 , -1.56610693,  0.57183099,  0.78684529],
       [ 1.2669898 ,  0.82737724, -0.25482473, -0.48885426],
       …,
       [-0.78927234,  0.82737724,         nan, -0.17626324],
       [ 1.2669898 , -1.56610693, -0.25482473, -0.04438104],
       [-0.78927234,  0.82737724,  0.15850313, -0.49237783]])
```

[ ]:
```
pd.DataFrame(df_scaled)
```

[ ]:

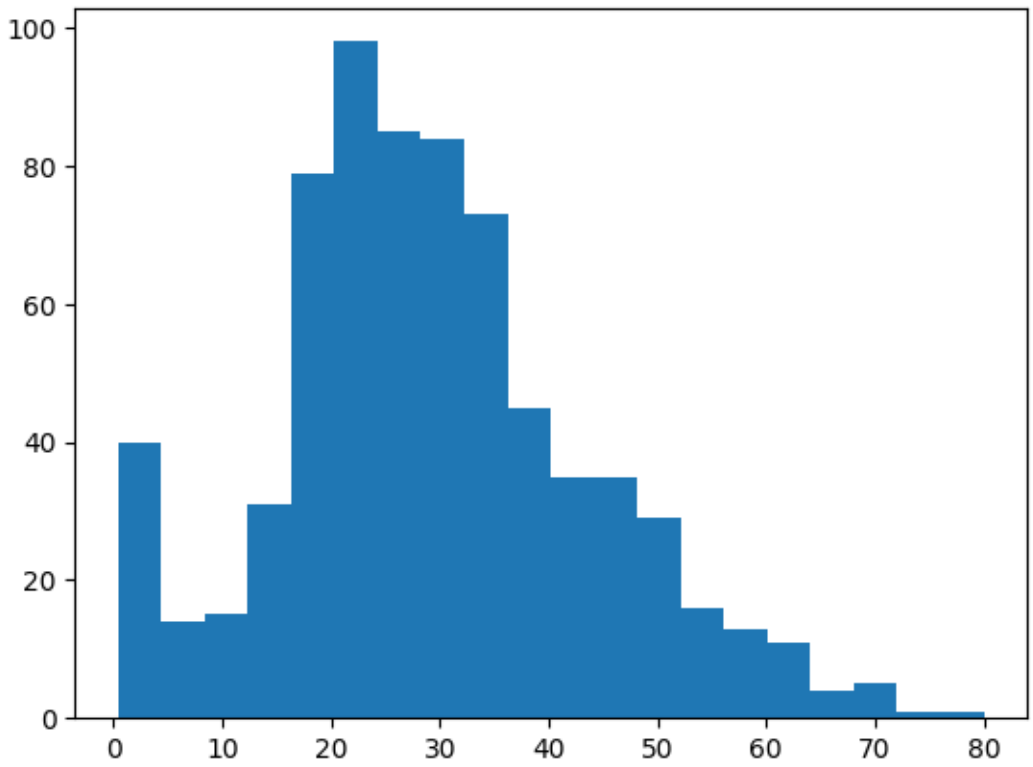
	0	1	2	3
0	-0.789272	0.827377	-0.530377	-0.502445
1	1.266990	-1.566107	0.571831	0.786845
2	1.266990	0.827377	-0.254825	-0.488854
3	1.266990	-1.566107	0.365167	0.420730
4	-0.789272	0.827377	0.365167	-0.486337
..	…	…	…	…
886	-0.789272	-0.369365	-0.185937	-0.386671
887	1.266990	-1.566107	-0.737041	-0.044381
888	-0.789272	0.827377	NaN	-0.176263
889	1.266990	-1.566107	-0.254825	-0.044381
890	-0.789272	0.827377	0.158503	-0.492378

[891 rows x 4 columns]

The transformation is taking placed based on each distinct field

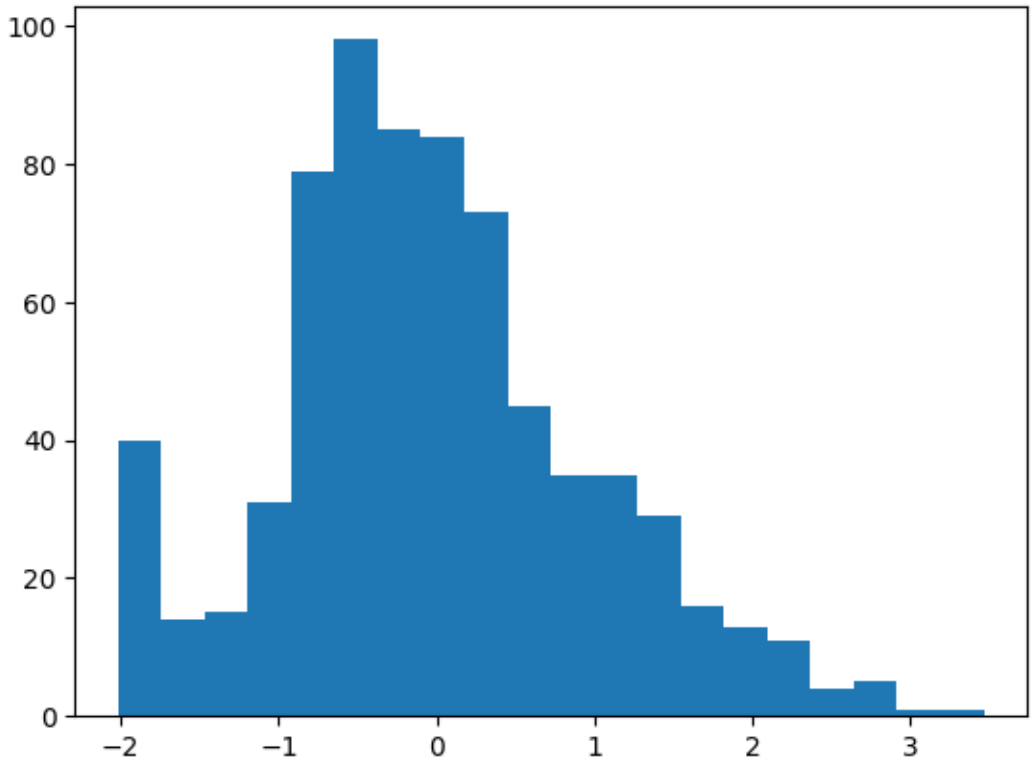
[ ]:
```
plt.hist(df['Age'],bins=20)
```

[ ]:
```
(array([40., 14., 15., 31., 79., 98., 85., 84., 73., 45., 35., 35., 29.,
        16., 13., 11.,  4.,  5.,  1.,  1.]),
 array([ 0.42 ,  4.399,  8.378, 12.357, 16.336, 20.315, 24.294, 28.273,
        32.252, 36.231, 40.21 , 44.189, 48.168, 52.147, 56.126, 60.105,
        64.084, 68.063, 72.042, 76.021, 80.   ]),
 <BarContainer object of 20 artists>)
```



[ ]:
```
plt.hist(df_scaled[:,2],bins=20)
```

[ ]:
```
(array([40., 14., 15., 31., 79., 98., 85., 84., 73., 45., 35., 35., 29.,
        16., 13., 11.,  4.,  5.,  1.,  1.]),
 array([-2.01697919, -1.74287393, -1.46876867, -1.1946634 , -0.92055814,
        -0.64645288, -0.37234762, -0.09824236,  0.1758629 ,  0.44996816,
         0.72407342,  0.99817868,  1.27228395,  1.54638921,  1.82049447,
         2.09459973,  2.36870499,  2.64281025,  2.91691551,  3.19102077,
         3.46512604]),
 <BarContainer object of 20 artists>)
```



2. MinMax Scaling Aim of this scaling is to transform/scale the values between 0 to 1 / 0 and 1 Works well with DL techniques such as CNN

X_scaled = ((X - X.min) / (X.max-X.min))

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
min_max = MinMaxScaler()
df_min_max = pd.DataFrame(min_max.fit_transform(df), columns=df.columns)
df_min_max
```

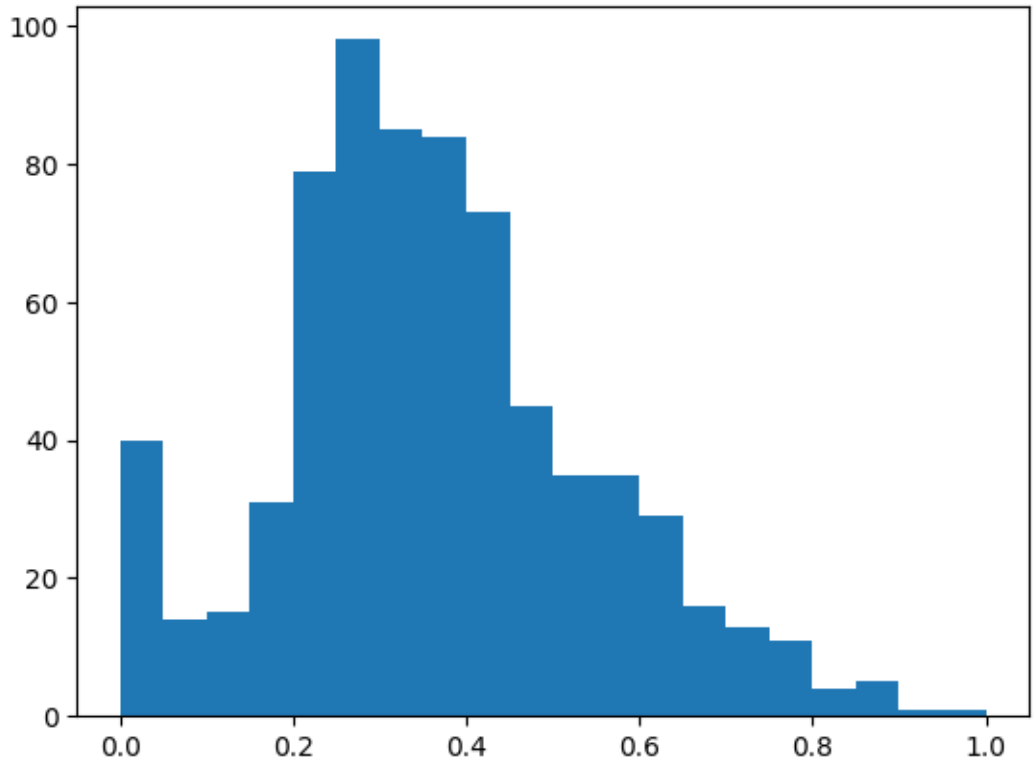
[ ]:

	Survived	Pclass	Age	Fare
0	0.0	1.0	0.271174	0.014151
1	1.0	0.0	0.472229	0.139136
2	1.0	1.0	0.321438	0.015469
3	1.0	0.0	0.434531	0.103644
4	0.0	1.0	0.434531	0.015713
..	…	…	…	…
886	0.0	0.5	0.334004	0.025374
887	1.0	0.0	0.233476	0.058556
888	0.0	1.0	NaN	0.045771
889	1.0	0.0	0.321438	0.058556
890	0.0	1.0	0.396833	0.015127

```
[891 rows x 4 columns]
```

[ ]:
```
plt.hist(df_min_max['Age'],bins=20)
```

[ ]:
```
(array([40., 14., 15., 31., 79., 98., 85., 84., 73., 45., 35., 35., 29.,
        16., 13., 11.,  4.,  5.,  1.,  1.]),
 array([0.  , 0.05, 0.1 , 0.15, 0.2 , 0.25, 0.3 , 0.35, 0.4 , 0.45, 0.5 ,
        0.55, 0.6 , 0.65, 0.7 , 0.75, 0.8 , 0.85, 0.9 , 0.95, 1.  ]),
 <BarContainer object of 20 artists>)
```



[ ]:

[ ]:

3. Mean Normalised

Formula: X(scaled)= (X i - X $mean$)/ Standard Deviation

[ ]:
```
df_mean_normalized = (df - df.mean()) / df.std()
print(df_mean_normalized)
```

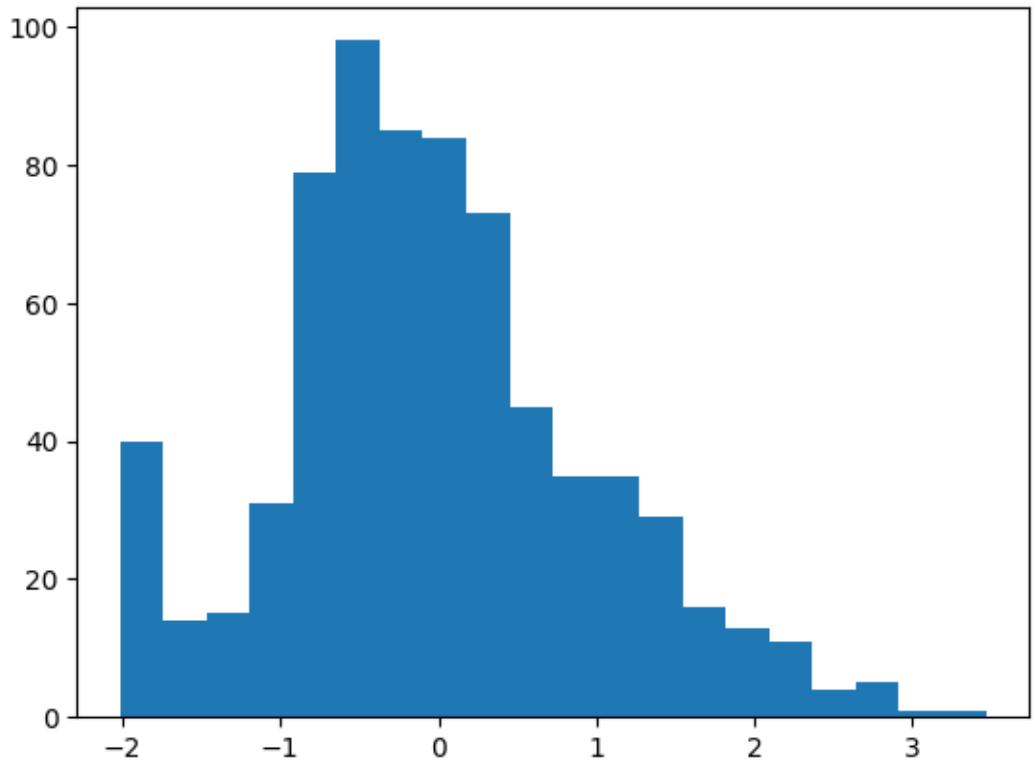
```
     Survived    Pclass       Age      Fare
0   -0.788829  0.826913 -0.530005 -0.502163
```

```
1    1.266279 -1.565228  0.571430  0.786404
2    1.266279  0.826913 -0.254646 -0.488580
3    1.266279 -1.565228  0.364911  0.420494
4   -0.788829  0.826913  0.364911 -0.486064
..        …        …        …        …
886 -0.788829 -0.369158 -0.185807 -0.386454
887  1.266279 -1.565228 -0.736524 -0.044356
888 -0.788829  0.826913       NaN -0.176164
889  1.266279 -1.565228 -0.254646 -0.044356
890 -0.788829  0.826913  0.158392 -0.492101

[891 rows x 4 columns]
```

[ ]:
```
plt.hist(df_mean_normalized['Age'],bins=20)
```

[ ]:
```
(array([40., 14., 15., 31., 79., 98., 85., 84., 73., 45., 35., 35., 29.,
        16., 13., 11.,  4.,  5.,  1.,  1.]),
 array([-2.01556624, -1.741653  , -1.46773976, -1.19382651, -0.91991327,
        -0.64600003, -0.37208678, -0.09817354,  0.1757397 ,  0.44965295,
         0.72356619,  0.99747944,  1.27139268,  1.54530592,  1.81921917,
         2.09313241,  2.36704565,  2.6409589 ,  2.91487214,  3.18878538,
         3.46269863]),
 <BarContainer object of 20 artists>)
```



4. Max Absolute Scaling:

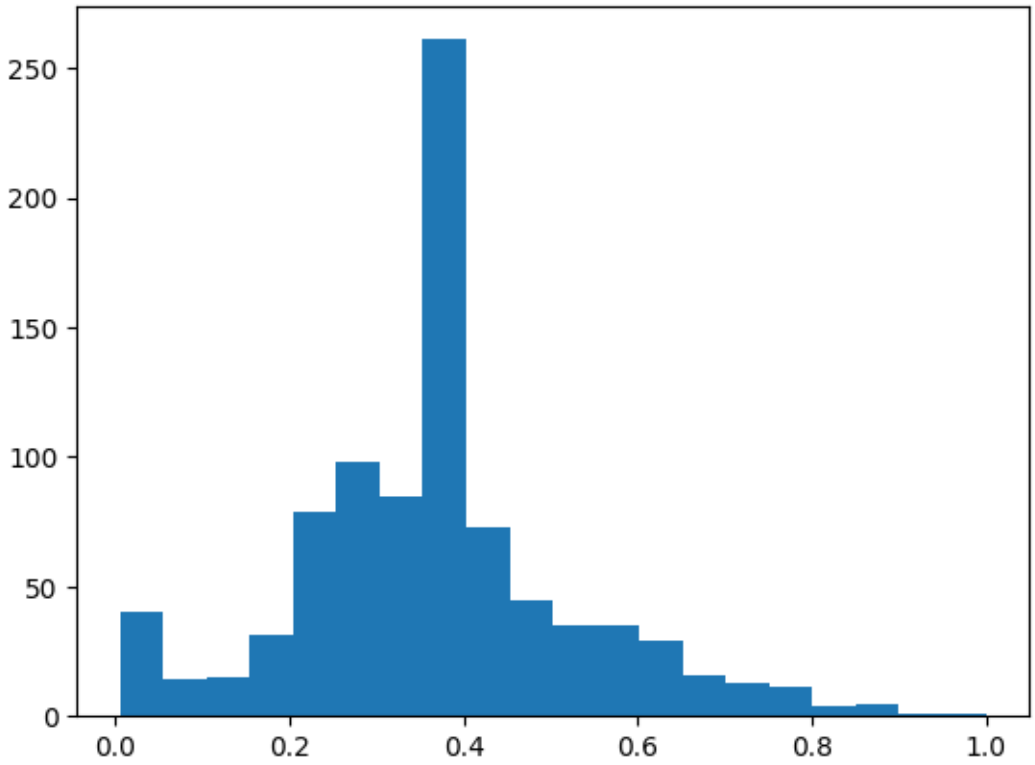
Formula: $\mathbf{X}$(scaled)- $\mathbf{X}$ /max(|$\mathbf{X}$|)

[ ]:
```
# max Absolute
from sklearn import preprocessing
df_max_abs_scaled = df / df.abs().max()
print(df_max_abs_scaled)
plt.hist(df_max_abs_scaled['Age'], bins=20)
```

```
     Survived    Pclass       Age      Fare
0         0.0  1.000000  0.275000  0.014151
1         1.0  0.333333  0.475000  0.139136
2         1.0  1.000000  0.325000  0.015469
3         1.0  0.333333  0.437500  0.103644
4         0.0  1.000000  0.437500  0.015713
..        …       …        …        …
886       0.0  0.666667  0.337500  0.025374
887       1.0  0.333333  0.237500  0.058556
888       0.0  1.000000  0.371239  0.045771
889       1.0  0.333333  0.325000  0.058556
890       0.0  1.000000  0.400000  0.015127

[891 rows x 4 columns]
```

[ ]:
```
(array([ 40.,  14.,  15.,  31.,  79.,  98.,  85., 261.,  73.,  45.,  35.,
         35.,  29.,  16.,  13.,  11.,   4.,   5.,   1.,   1.]),
 array([0.00525  , 0.0549875, 0.104725 , 0.1544625, 0.2042   , 0.2539375,
        0.303675 , 0.3534125, 0.40315  , 0.4528875, 0.502625 , 0.5523625,
        0.6021   , 0.6518375, 0.701575 , 0.7513125, 0.80105  , 0.8507875,
        0.900525 , 0.9502625, 1.       ]),
 <BarContainer object of 20 artists>)
```



5. Robust Scaler Used to scale features according to median and quantiles (IQR)

Best in presence of outliers.

IQR = Q3 - Q1 X_scaled = (X-X.median)/IQR

[ ]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

df_robust_scaled = (df - df.median()) / IQR
print(df_robust_scaled)
plt.hist(df_robust_scaled['Age'], bins=20)
```

```
     Survived  Pclass       Age      Fare
0         0.0     0.0 -0.592240 -0.312011
1         1.0    -2.0  0.638529  2.461242
2         1.0     0.0 -0.284548 -0.282777
3         1.0    -2.0  0.407760  1.673732
4         0.0     0.0  0.407760 -0.277363
..        …     …       …        …
886       0.0    -1.0 -0.207624 -0.062981
887       1.0    -2.0 -0.823009  0.673281
888       0.0     0.0  0.000000  0.389604
```

```
889       1.0    -2.0 -0.284548  0.673281
890       0.0     0.0  0.176991 -0.290356

[891 rows x 4 columns]
```

```
[ ]: (array([ 40.,  14.,  15.,  31.,  79.,  98.,  85., 261.,  73.,  45.,  35.,
              35.,  29.,  16.,  13.,  11.,   4.,   5.,   1.,   1.]),
      array([-2.25223982, -1.9461629 , -1.64008597, -1.33400905, -1.02793213,
             -0.7218552 , -0.41577828, -0.10970136,  0.19637557,  0.50245249,
              0.80852941,  1.11460633,  1.42068326,  1.72676018,  2.0328371 ,
              2.33891403,  2.64499095,  2.95106787,  3.2571448 ,  3.56322172,
              3.86929864]),
      <BarContainer object of 20 artists>)
```