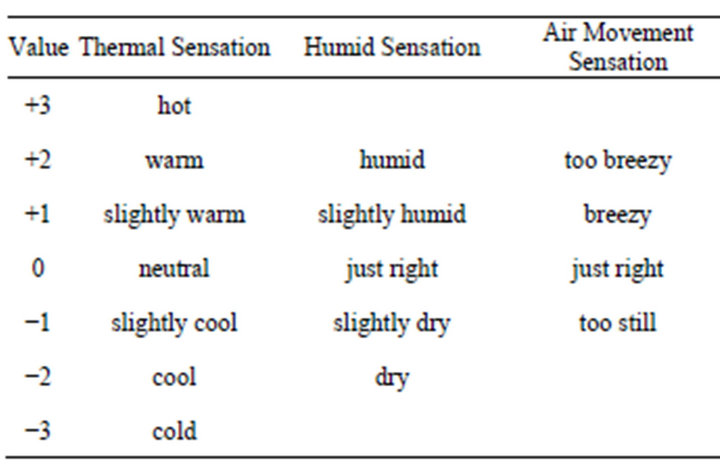
For this task you will be applying machine learning models (both regression and classification) to the dataset which contains information about various individuals, their clothing, and its properties along with other atmospheric elements such as temperature, pressure humidity etc. The users also provided feedback on if they feel cold or not. The feedback (through AMV and PMV) which is based on the following mapping:

The following table shows the mapping of sensations:



**The dataset is given in an excel file named CollectedData.xlsx, see sheet 2 of excel file.** The dimension names (column headers) are not mentioned in the given file. The table below describes the columns which will be of your interest.

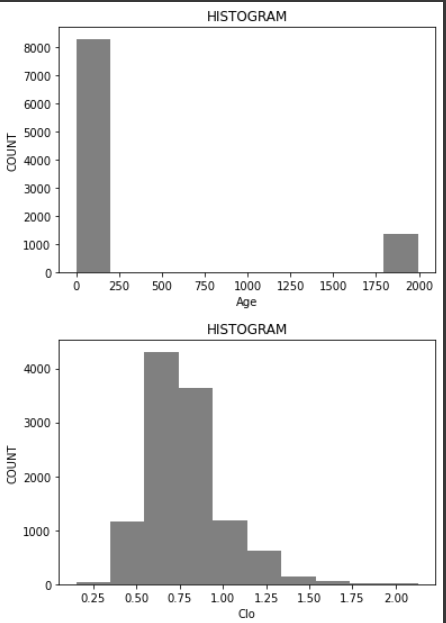
|  |  |  |
| --- | --- | --- |
| **Column number** | **Feature Name** | **Feature Description** |
| 3 | Age | Age |
| 22 | Clo | Clothing insulation |
| 19 | Met | Met Rate |
| 26 | Dewpt | Dewpt |
| 27 | PlaneRadTemp | plane radiant temperature |
| 37 | Ta | Average air temperature |
| 38 | Tmrt | Average mean radiant temperature |
| 40 | Vel | Air Velocity |
| 42 | AirTurb | Air Turbulance |
| 43 | Pa | Vapor Pressure |
| 44 | Rh | Humidity |
| 74 | TaOutdoor | Outdoor Air Temperature |
| 77 | RhOutdoor | Outdoor Humidity |
| 8 | AMV | Classification response variable |
| 49 | PMV | Regression response variable |

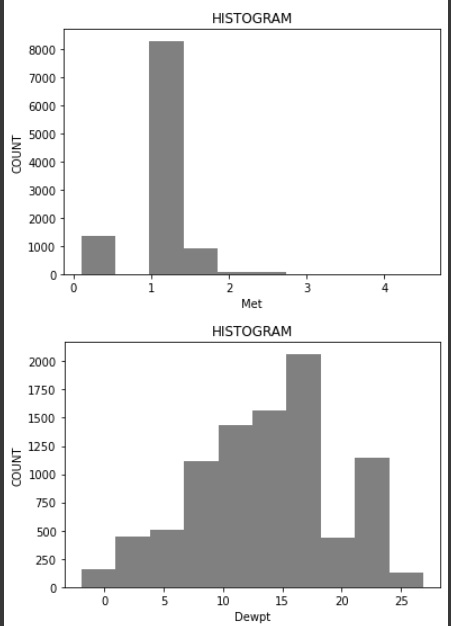
***Part A. Preprocessing***

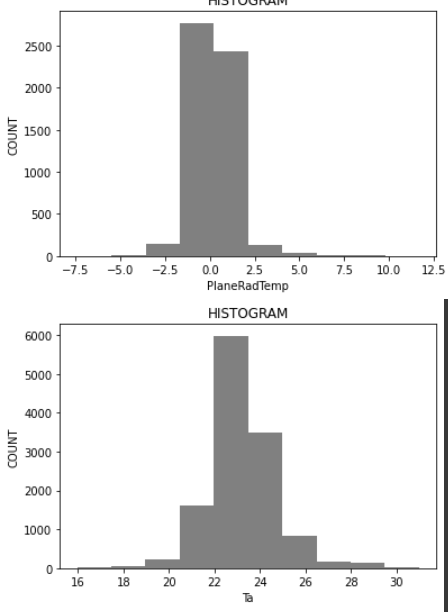
**1. In this step, you are required to apply the preprocessing steps that you’ve covered in the course. Specifically, for each of the input dimension, fill in the following (add rows and complete the table for all input dimensions).**

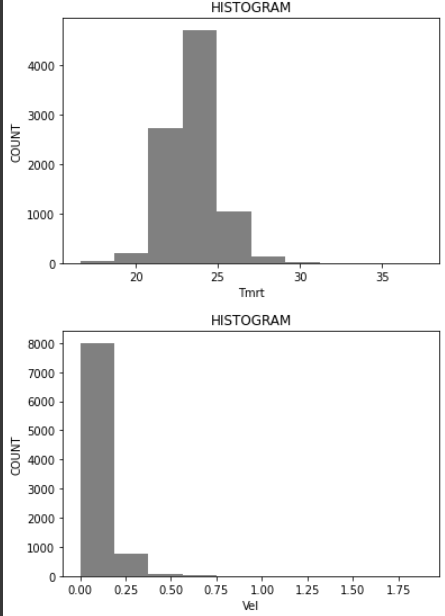
|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **count** | **mean** | **std** | **min** | **max** | **NULLS** | **dtypes** | **median** | **mode** | **variance** |
| **Age** | 9650 | 308.6372 | 680.1151 | 0 | 1996 | 2916 | float64 | 35 | 24 | 462556.6 |
| **Clo** | 11160 | 0.778492 | 0.221992 | 0.15 | 2.13 | 1406 | float64 | 0.7517 | 0.77 | 0.049281 |
| **Met** | 10679 | 1.066003 | 0.428978 | 0.1 | 4.5 | 1887 | float64 | 1.1 | 1 | 0.184022 |
| **Dewpt** | 9014 | 13.62145 | 5.903044 | -1.953 | 26.89675 | 3552 | float64 | 14.1 | 17.4 | 34.84593 |
| **PlaneRadTemp** | 5544 | 0.217785 | 1.041164 | -7.42 | 11.7 | 7022 | float64 | 0.2 | 0.3 | 1.084022 |
| **Ta** | 12546 | 23.17886 | 1.43339 | 15.96 | 31 | 20 | float64 | 23.13667 | 23.2 | 2.054606 |
| **Tmrt** | 8865 | 23.45026 | 1.502953 | 16.61 | 37.445 | 3701 | float64 | 23.35844 | 22.5 | 2.258867 |
| **Vel** | 8866 | 0.112439 | 0.079041 | 0 | 1.88 | 3700 | float64 | 0.1 | 0.1 | 0.006248 |
| **AirTurb** | 6965 | 18.26587 | 25.04111 | 0 | 102.45 | 5601 | float64 | 0.5 | 0.5 | 627.0571 |
| **Pa** | 7910 | 5.123996 | 8.156136 | 0 | 27.7 | 4656 | float64 | 1.550667 | 2.1 | 66.52256 |
| **Rh** | 12531 | 42.5292 | 15.06108 | 7.4 | 79.3 | 35 | float64 | 43.28 | 64 | 226.836 |
| **TaOutdoor** | 11198 | 17.17458 | 10.66507 | -24.9 | 32.35 | 1368 | float64 | 18.2 | 27.55556 | 113.7437 |
| **RhOutdoor** | 12547 | 61.10037 | 24.7039 | 0 | 100.35 | 19 | float64 | 68.7958 | 0 | 610.2825 |
| **AMV** | 12511 | 0.100735 | 1.102099 | -3 | 3 | 55 | float64 | 0 | 0 | 1.214621 |
| **PMV** | 11870 | -0.07368 | 0.538016 | -4.17 | 2.5 | 696 | float64 | -0.03 | 0.1 | 0.289461 |

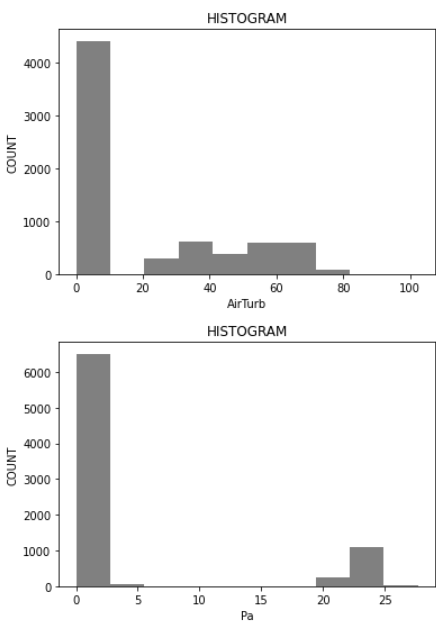
**2. For each of the input dimension, plot histogram and comment the type of distribution the dimension exhibits. Further, visualize each dimension using a Box Plot. Specifically, for each of the input dimension, you’re required to fill the following table (duplicate it for each of the 15 dimensions).**

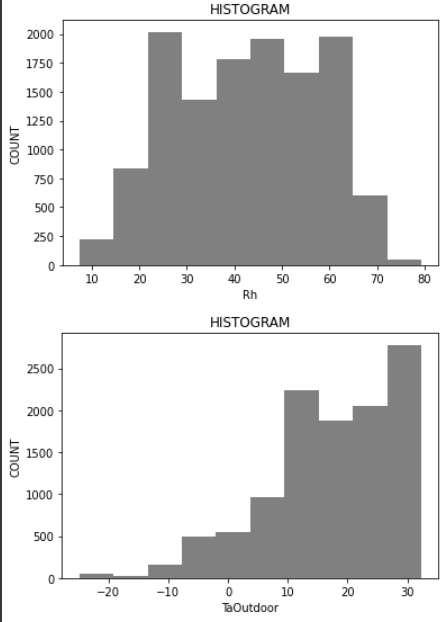


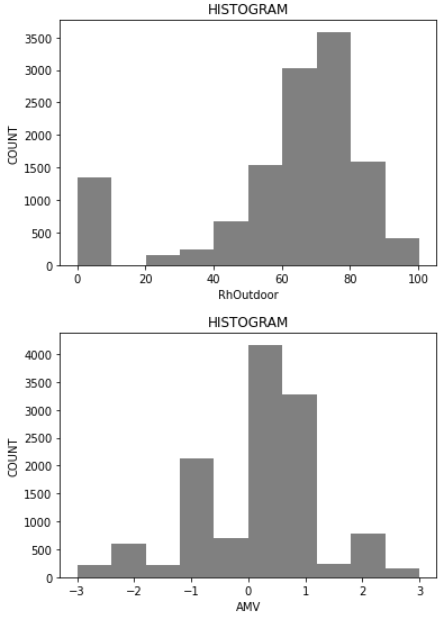


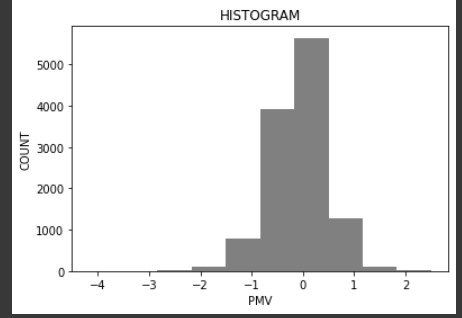




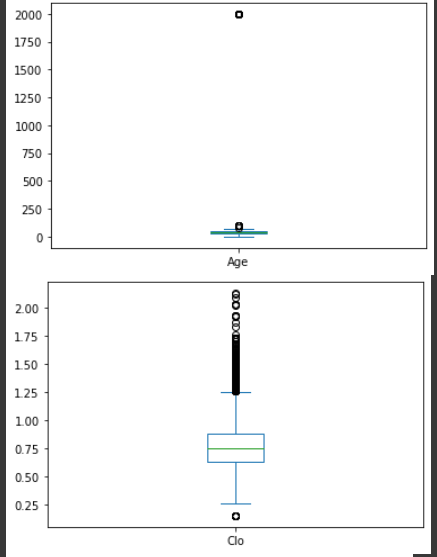


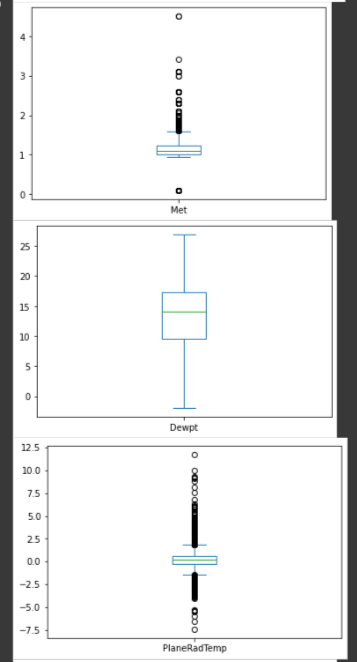


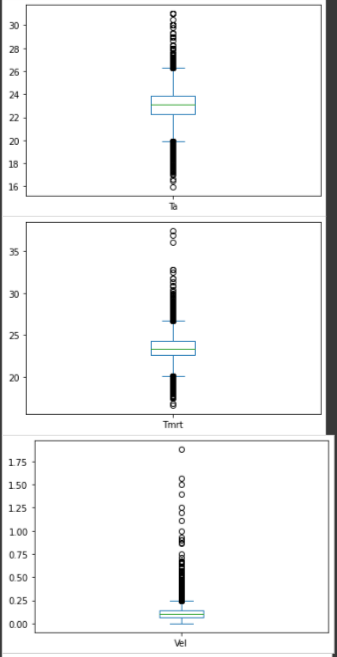


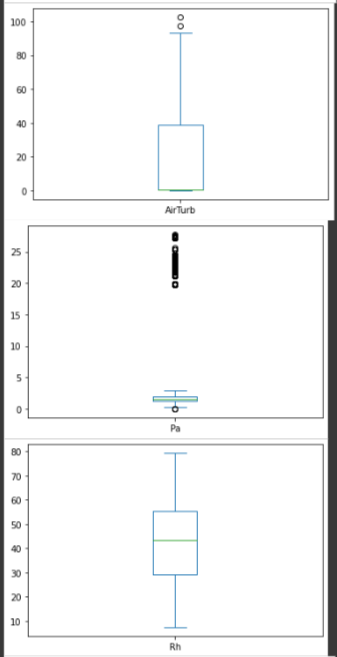


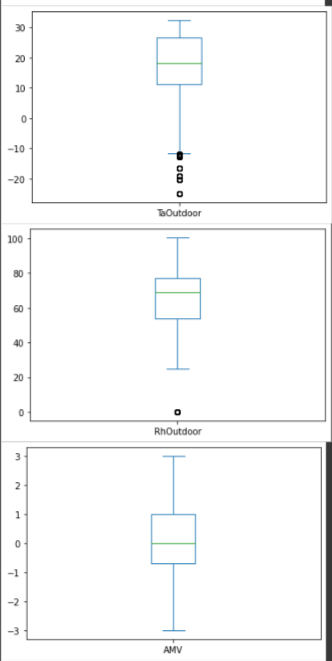
BOXE PLOTS:

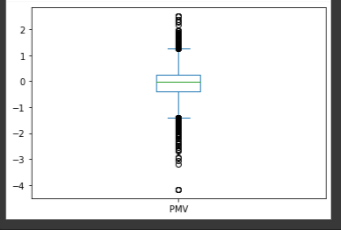












**3. Find the missing values in each of the dimension (do this for both input and output dimensions), and fill these using an “appropriate” methodology that we’ve discussed in the class. You may also choose to drop a certain sample based on your analysis. Mention your approach and its justification.**

|  |  |  |  |
| --- | --- | --- | --- |
| Dim Name | Number of Missing Values | Filled using OR Dropped | Reason for selecting a certain approach |
| **Age** | 2916 | Filled with mediam | Too many outliers |
| **Clo** | 1406 | Filled with mean | Too low variance |
| **Met** | 1887 | Filled with mean | Too low variance |
| **Dewpt** | 3552 | Filled with median | High variance |
| **PlaneRadTemp** | 7022 | Column dropped | More than 50 percent is null |
| **Ta** | 20 | Nulls dropped | Values are quite less |
| **Tmrt** | 3701 | Filled with mean | Low variance |
| **Vel** | 3700 | Filled with mean | Low variance |
| **AirTurb** | 5601 | Column dropped | Almost 50 percent is null |
| **Pa** | 4656 | Filled with median | High variance |
| **Rh** | 35 | Nulls dropped | Values are quite less |
| **TaOutdoor** | 1368 | Filled with median | High variance |
| **RhOutdoor** | 19 | Nulls dropped | Values are quite less |
| **AMV** | 55 | Nulls dropped | Response variable |
| **PMV** | 696 | Nulls dropped | Response variable |

**4. For each of the dimension, find out the outliers (noisy data) and handle these appropriately.**

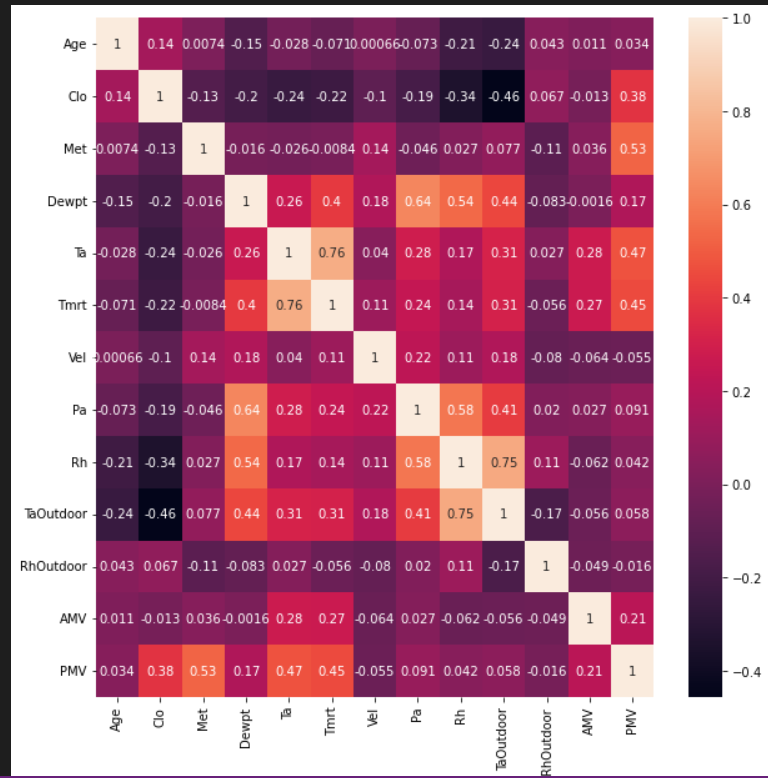
|  |  |  |  |
| --- | --- | --- | --- |
| Dim Name | Number of Outliers | Smooth using/ Dropped | Reason for selecting a certain approach |
| **Age** | 696 | dropped | All values accounted to a fraction of data |
| **Clo** | 155 | dropped | All values accounted to a fraction of data |
| **Met** | 802 | dropped | All values accounted to a fraction of data |
| **Dewpt** | 9 | dropped | All values accounted to a fraction of data |
| **Ta** | 209 | dropped | All values accounted to a fraction of data |
| **Tmrt** | 193 | dropped | All values accounted to a fraction of data |
| **Vel** | 131 | dropped | All values accounted to a fraction of data |
| **Pa** | 696 | dropped | All values accounted to a fraction of data |
| **Rh** | 0 | dropped | All values accounted to a fraction of data |
| **TaOutdoor** | 80 | dropped | All values accounted to a fraction of data |
| **RhOutdoor** | 696 | dropped | All values accounted to a fraction of data |
| **AMV** | 0 | dropped | All values accounted to a fraction of data |
| **PMV** | 106 | dropped | All values accounted to a fraction of data |
|  |  |  |  |
|  |  |  |  |

**5. Using the variance that you’ve calculated above, for each dimension, comment whether you’ll select the input dimension or no. (don’t drop a dimension at this point)**

|  |  |  |
| --- | --- | --- |
| **Age** | 212775.6 | No |
| **Clo** | 0.046331 | Yes,variance too low |
| **Met** | 0.111062 | Yes,variance too low |
| **Dewpt** | 21.95075 | No |
| **Ta** | 2.116603 | No |
| **Tmrt** | 1.686254 | No |
| **Vel** | 0.004678 | Yes,variance too low |
| **Pa** | 26.87774 | No |
| **Rh** | 216.8419 | No |
| **TaOutdoor** | 107.0955 | No |
| **RhOutdoor** | 428.8329 | No |
| **AMV** | 1.219829 | No |
| **PMV** | 0.284154 | No |

Variance threshold = 0.15

**6A. Create a correlation matrix (Heat Map) for all the dimensions (input and output).**

****

**6B. Using the above correlation matrix, comment what are the most informative dimensions, and which are the least. Note that, be careful since we have two response variables in the dataset (i.e., PMV and AMV regression and classification respectively)**

Most informative = (Ta, Tmrt,Clo,Met)

Least informative = (TaOutdoor) because it is highly correlated with other features and least correlated with the response variables

[9.20718357, 9.20782152, 9.23121228, -inf, 9.2391394 , 9.23939942, 9.13922971, 9.21684158, 9.18848707, -inf, 9.2208708 , -inf, -inf]

**7. Apply entropy followed by information gain on the selected columns. Specify your selection criteria.**

|  |  |
| --- | --- |
| **Age** | 9.20718357 |
| **Clo** | 9.20782152 |
| **Met** | 9.23121228 |
| **Dewpt** | inf |
| **Ta** | 9.2391394 |
| **Tmrt** | 9.23939942 |
| **Vel** | 9.13922971 |
| **Pa** | 9.21684158 |
| **Rh** | 9.18848707 |
| **TaOutdoor** | inf |
| **RhOutdoor** | 9.2208708 |
| **AMV** | inf |
| **PMV** | inf |

***Part B. Applying Algorithms***

**1. For this part, split the data randomly into 80/20 percent. Where 80% represents the training data. Also normalize the dataset as you see fit.**

**2A. Apply forward selection, considering PMV as response variable and Multilinear regression as machine learning model. Create a table, that mentions dimensions, and performance achieved. Which is the optimal feature set, and why.**

|  |  |
| --- | --- |
| Feature Vector | Performance achieved |
| ['Age', 'Clo', 'Met', 'Dewpt', 'Ta', 'Tmrt', 'Pa', 'Rh', 'RhOutdoor'] | 0.9076758323112847 |

**2B. Apply backward selection, considering PMV as response variable and Multilinear regression as machine learning model. Create a table, that mentions dimensions, and performance achieved. Which is the optimal feature set, and why.**

|  |  |
| --- | --- |
| Feature Vector | Performance achieved |
| ['Age', 'Clo', 'Met', 'Dewpt', 'Ta', 'Tmrt', 'Pa', 'Rh', 'RhOutdoor'] | 0.9076758323112847 |

**3A. Apply forward selection, considering AMV as response variable and Logistic regression as machine learning model. Create a table, that mentions dimensions, and performance achieved. Which is the optimal feature set, and why.**

|  |  |
| --- | --- |
| Feature Vector | Performance achieved |
| Model not fitting because amv is continuous variable |  |

**3B. Apply backward selection, considering AMV as response variable and Logistic regression as machine learning model. Create a table, that mentions dimensions, and performance achieved. Which is the optimal feature set, and why.**

|  |  |
| --- | --- |
| Feature Vector | Performance achieved |
| Model not fitting because amv is continuous variable |

**4. Using the optimal feature vector that you’ve figured out from your analysis above, apply 3-fold cross validation for both regression and classification problems (PMV and AMV respectively). Write down the optimal parameters values for each of the model. Further, plot confusion matrix for the classification part.**