Data Preprocessing

Data Transformation

Data Transformation

- The data are transformed or consolidated into the forms appropriate for data modelling using machine learning
- Data Transformation involve
  - Smoothing:
    - Used for removing noise or reducing the effect of noise
    - Techniques: Binning, Regression, Clustering
  - Aggregation:
    - Summery or aggregation operation are applied to the data
    - Analysis of data at multiple granularity
      - Example: Daily sales data, Monthly sales data (aggregated on daily data)
  - Attribute construction (feature construction):
    - New attributes are constructed from the raw-data to help mining process
  - Normalization and standardization

Attribute Normalization

- In the context of machine learning, it is termed as feature normalization
- An attribute is normalised by scaling its value so that they fall within a small specified range (for example 0.0 to 1.0)
- Normalization is particularly useful for classification algorithms involving distance measurements and clustering
- For distance based approaches, normalization helps prevent attributes with large ranges from overweighting attributes with smaller ranges

Illustration

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	23500.00	8
S002	23500.00	6
S003	22879.00	2
S004	2300.00	4
S005	34678.00	5
S006	15687.00	8
S007	18945.00	8
S008	8750.00	2
S009	37489.00	4
S010	73567.00	2
S011	52789.00	4
S012	2900.00	3
S013	6570	3
S014	21000.00	2
min:	**2300.00**	**2**
max:	**73567.00**	**8**

y_1	y_2
23000.00	6.5

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(23500.00 - 23000.00)^2 + (8 - 6.5)^2$

ED1 = **250002.25**

Illustration

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	23500.00	8
S002	23500.00	6
S003	22879.00	2
S004	2300.00	4
S005	34678.00	5
S006	15687.00	8
S007	18945.00	8
S008	8750.00	2
S009	37489.00	4
S010	73567.00	2
S011	52789.00	4
S012	2900.00	3
S013	6570	3
S014	21000.00	2
min:	**2300.00**	**2**
max:	**73567.00**	**8**

y_1	y_2
23000.00	6.5

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

$ED1 = (23500.00 - 23000.00)^2 + (8 - 6.5)^2$

ED1 = **250002.25**

$ED1 = (23500.00 - 23000.00)^2 + (6 - 6.5)^2$

ED1 = **250000.25**

Illustration

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	23500.00	8
S002	23500.00	6
S003	22879.00	2
S004	2300.00	4
S005	34678.00	5
S006	15687.00	8
S007	18945.00	8
S008	8750.00	2
S009	37489.00	4
S010	73567.00	2
S011	52789.00	4
S012	2900.00	3
S013	6570	3
S014	21000.00	2
min:	**2300.00**	**2**
max:	**73567.00**	**8**

y_1	y_2
23000.00	6.5

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(23500.00 - 23000.00)^2 + (8 - 6.5)^2$
ED1 = **250002.25**

ED1 = $(23500.00 - 23000.00)^2 + (6 - 6.5)^2$
ED1 = **250000.25**

ED3 = $(22879.00 - 23000.00)^2 + (2 - 6.5)^2$
ED3 = **14661.25**

Attribute Normalization: Min-Max Normalization

- It performs a linear transformation on the original data
- The transformed data is the scaled version of the original data so that they fall within a small specified range
- Each numeric attributes in a data are normalised separately
- Steps:
  - Compute minimum (mn_A) and maximum (mx_A) values of an attribute A
  - Specify the new minimum (new_mn_A) and new maximum range (new_mx_A)
  - Min-Max normalization maps a value, x of attribute A to $\hat{x}$ in the specified range by computing

$$\hat{x} = \frac{x - mn_A}{mx_A - mn_A}(new\_mx_A - new\_mn_A) + new\_mn_A$$

Attribute Normalization: Min-Max Normalization

- When new minimum (new_mn_A) and new maximum range (new_mx_A) is 0 and 1 respectively, then the data is scaled to 0.0 to 1.0 range
  - Min-Max normalization maps a value, x of attribute A to $\hat{x}$ in the specified range by computing

$$\hat{x} = \frac{x - mn_A}{mx_A - mn_A}$$

Min-Max Normalization during Model Building

- Model building and prediction using machine learning involve two stages:
  - Training stage: Model building
  - Test stage: Prediction using the built model
- Training stage: Normalise each attribute using Min-Max normalization by using the minimum and maximum values from respective attributes
- Test stage: Normalise each test records (samples) using the minimum and maximum values from respective attributes obtained during training stage

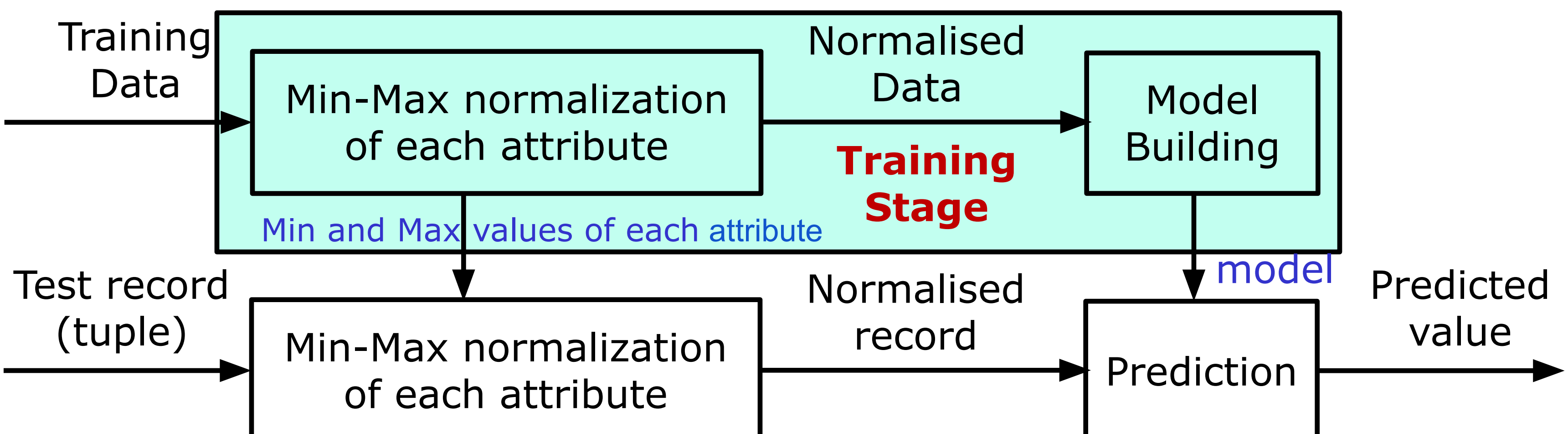


Illustration of Min-Max Normalization

	Temperature	Humidity	Rain
1	Temperature	Humidity	Rain
2	25.46875	82.1875	6.75
3	26.19298	83.14912	1762
4	25.17021	85.34043	653
5	24.29851	87.68657	963
6	24.06923	87.64615	254
7	21.20779	95.94805	340
8	23.48571	96.17143	38.3
9	21.79487	98.58974	29.3
10	25.09346	88.3271	4.5
11	25.39423	90.43269	113
12	23.89076	94.53782	736
13	22.5098	99	608
14	22.904	98	718
15	21.72464	99	513

Temperature	Humidity	Rain
0.85472	0.00000	0.00128
1.00000	0.05720	1.00000
0.79484	0.18753	0.36876
0.61998	0.32708	0.54545
0.57399	0.32468	0.14213
0.00000	0.81847	0.19078
0.45694	0.83176	0.01921
0.11776	0.97560	0.01408
0.77944	0.36518	0.00000
0.83978	0.49042	0.06146
0.53819	0.73459	0.41613
0.26118	1.00000	0.34315
0.34025	0.94052	0.40589
0.10368	1.00000	0.28937

	Temperature	Humidity	Rain	Temperature	Humidity	Rain
min:	21.20779	82.187	4.5	0.000	0.000	0.000
max:	26.19298	99	1762	1.000	1.000	1.000

Illustration of Min-Max Normalization

Salesman-ID	Total sales (Rs)	Score for sale
S001	23500.00	8
S002	23500.00	6
S003	22879.00	2
S004	2300.00	4
S005	34678.00	5
S006	15687.00	8
S007	18945.00	8
S008	8750.00	2
S009	37489.00	4
S010	73567.00	2
S011	52789.00	4
S012	2900.00	3
S013	6570	3
S014	21000.00	2
min:	**2300.00**	**2**
max:	**73567.00**	**8**

→

Salesman-ID	Total sales (Rs)	Score for sale
S001	0.2975	1.0000
S002	0.2975	0.6667
S003	0.2888	0.0000
S004	0.0000	0.3333
S005	0.4543	0.5000
S006	0.1878	1.0000
S007	0.2336	0.6667
S008	0.0905	0.0000
S009	0.4938	0.3333
S010	1.0000	0.0000
S011	0.7084	0.3333
S012	0.0084	0.1667
S013	0.0599	0.1667
S014	0.2624	0.0000
	0.0000	**0.0000**
	1.0000	**1.0000**

Illustration of Min-Max Normalization

Salesman-ID	Total sales (Rs)	Score for sale
S001	0.2975	1.0000
S002	0.2975	0.6667
S003	0.2888	0.0000
S004	0.0000	0.3333
S005	0.4543	0.5000
S006	0.1878	1.0000
S007	0.2336	0.6667
S008	0.0905	0.0000
S009	0.4938	0.3333
S010	1.0000	0.0000
S011	0.7084	0.3333
S012	0.0084	0.1667
S013	0.0599	0.1667
S014	0.2624	0.0000
min:	**0.0000**	**0.0000**
max:	**1.0000**	**1.0000**

23000.00	6.5

0.2905	0.75

Illustration of Min-Max Normalization

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	0.2975	1.0000
S002	0.2975	0.6667
S003	0.2888	0.0000
S004	0.0000	0.3333
S005	0.4543	0.5000
S006	0.1878	1.0000
S007	0.2336	0.6667
S008	0.0905	0.0000
S009	0.4938	0.3333
S010	1.0000	0.0000
S011	0.7084	0.3333
S012	0.0084	0.1667
S013	0.0599	0.1667
S014	0.2624	0.0000
min:	**0.0000**	**0.0000**
max:	**1.0000**	**1.0000**

y_1	y_2
0.2905	0.75

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(0.2975 - 0.2905)^2 + (1 - 0.75)^2$

ED1 = **0.06255**

Illustration of Min-Max Normalization

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	0.2975	1.0000
S002	0.2975	0.6667
S003	0.2888	0.0000
S004	0.0000	0.3333
S005	0.4543	0.5000
S006	0.1878	1.0000
S007	0.2336	0.6667
S008	0.0905	0.0000
S009	0.4938	0.3333
S010	1.0000	0.0000
S011	0.7084	0.3333
S012	0.0084	0.1667
S013	0.0599	0.1667
S014	0.2624	0.0000
min:	**0.0000**	**0.0000**
max:	**1.0000**	**1.0000**

y_1	y_2
0.2905	0.75

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d}(x_i - y_i)^2$$

ED1 = $(0.2975 - 0.2905)^2 + (1 - 0.75)^2$
ED1 = **0.06255**

ED2 = $(0.2975 - 0.2905)^2 + (0.6667 - 0.75)^2$
ED2 = **0.00699**

Illustration of Min-Max Normalization

Salesman-ID	x_1 Total sales (Rs)	x_2 Score for sale
S001	0.2975	1.0000
S002	0.2975	0.6667
S003	0.2888	0.0000
S004	0.0000	0.3333
S005	0.4543	0.5000
S006	0.1878	1.0000
S007	0.2336	0.6667
S008	0.0905	0.0000
S009	0.4938	0.3333
S010	1.0000	0.0000
S011	0.7084	0.3333
S012	0.0084	0.1667
S013	0.0599	0.1667
S014	0.2624	0.0000
min:	**0.0000**	**0.0000**
max:	**1.0000**	**1.0000**

y_1	y_2
0.2905	0.75

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(0.2975 - 0.2905)^2 + (1.0 - 0.75)^2$
ED1 = **0.06255**

ED2 = $(0.2975 - 0.2905)^2 + (0.6667 - 0.75)^2$
ED2 = **0.00699**

ED3 = $(0.2888 - 0.2905)^2 + (0.0 - 0.75)^2$
ED3 = **0.56250**

Attribute Normalization: Min-Max Normalization

- Min-Max normalization preserves the relationship among the original data values
- It is useful when data has varying ranges among attributes
- It is useful when machine learning (ML) algorithms we are using does not make any assumption about distribution of data
- It is useful when the actual minimum and maximum values for the attribute is known
- Disadvantage: “out-of-bound” error if a future input case for normalization falls outside the original range of attribute `A`
  - This situation arises when the actual minimum and maximum of attribute `A` is unknown

Data Standardization (z-score Normalization)

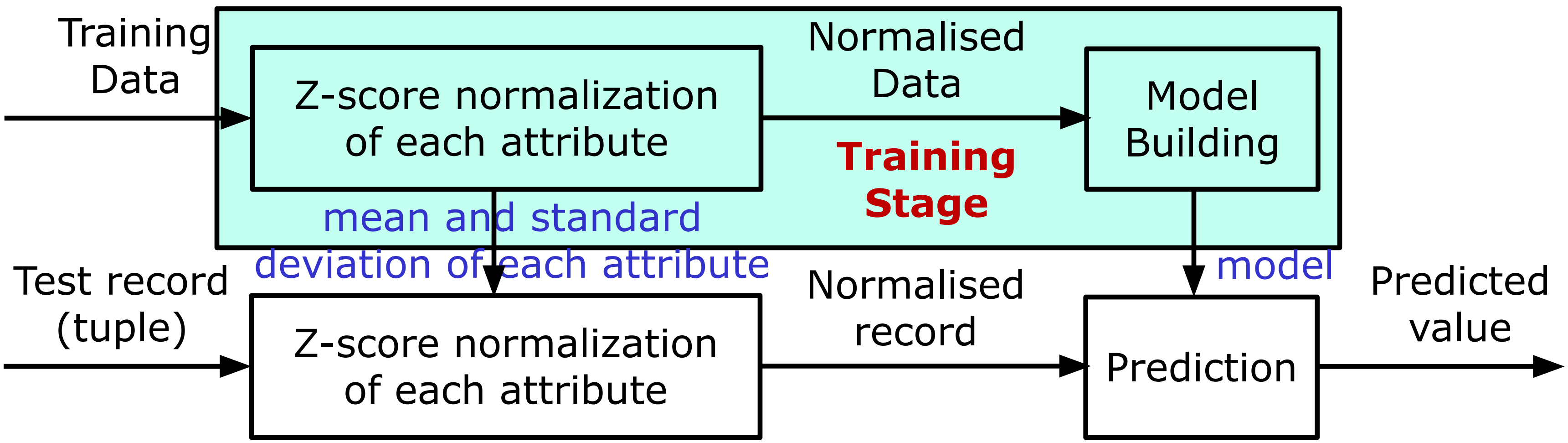
- The process of rescaling one or more attributes so that the transformed data have 0 mean and unit variance i.e. standard deviation of 1
- Standardization assumes that data is coming from Gaussian distribution
  - This assumption does not strictly have to be true, but this technique is more effective if your attribute distribution is Gaussian
- In this process, values of an attribute, A, are normalised based on the mean and standard deviation of A
  - Min-Max normalization maps a value, x of attribute A to $\hat{x}$ in the specified range by computing

$$\hat{x} = \frac{x-\mu_A}{\sigma_A}$$

- μ_A: mean of attribute A
- σ_A: standard deviation of attribute A

z-score Normalization during Model Building

- Model building and prediction using machine learning involve two stages:
  - Training stage: Model building
  - Test stage: Prediction using the built model
- Training stage: Normalise each attribute using z-score normalization by using the mean and standard deviation from respective attributes
- Test stage: Normalise each test records (samples) using the mean and standard deviation from respective attributes obtained during training stage



Data Standardization (z-score Normalization)

- This method of normalization is useful
  - when the actual minimum and maximum of attribute are unknown
  - when there are outliers that dominates the Min-Max normalization
  - when data follows Gaussian distribution (symmetric distribution)
- This method of normalization is useful when the ML algorithms make any assumptions of Gaussian distribution

Illustration of Data Standardization (z-score Normalization)

	Temperature	Humidity	Rain
2	25.46875	82.1875	6.75
3	26.19298	83.14912	1762
4	25.17021	85.34043	653
5	24.29851	87.68657	963
6	24.06923	87.64615	254
7	21.20779	95.94805	340
8	23.48571	96.17143	38.3
9	21.79487	98.58974	29.3
10	25.09346	88.3271	4.5
11	25.39423	90.43269	113
12	23.89076	94.53782	736
13	22.5098	99	608
14	22.904	98	718
15	21.72464	99	513
μ:	23.80035	91.86	481
σ:	1.58225	6.13	488

Temperature	Humidity	Rain
1.05444	-1.57673	-0.97166
1.51216	-1.41995	2.62269
0.86576	-1.06268	0.35088
0.31484	-0.68016	0.98680
0.16993	-0.68675	-0.46476
-1.63853	0.66679	-0.28965
-0.19886	0.70321	-0.90714
-1.26749	1.09749	-0.92558
0.81726	-0.57573	-0.97627
1.00735	-0.23244	-0.75508
0.05714	0.43686	0.52138
-0.81564	1.16438	0.25871
-0.56650	1.00134	0.48451
-1.31187	1.16438	0.06517
0.000	0.000	0.000
1	1	1

Illustration of Data Standardization (z-score Normalization)

Salesman-ID	Total sales (Rs)	Score for sale
S001	23500.00	8
S002	23500.00	6
S003	22879.00	2
S004	2300.00	4
S005	34678.00	5
S006	15687.00	8
S007	18945.00	8
S008	8750.00	2
S009	37489.00	4
S010	73567.00	2
S011	52789.00	4
S012	2900.00	3
S013	6570	3
S014	21000.00	2
μ :	**24611.00**	**4.36**
σ :	**19873.30**	**2.31**

Salesman-ID	Total sales (Rs)	Score for sale
S001	-0.06	1.58
S002	-0.06	0.71
S003	-0.09	-1.02
S004	-1.12	-0.15
S005	0.51	0.28
S006	-0.45	1.58
S007	-0.29	1.58
S008	-0.80	-1.02
S009	0.65	-0.15
S010	2.46	-1.02
S011	1.42	-0.15
S012	-1.09	-0.59
S013	-0.91	-0.59
S014	-0.18	-1.02
	0.00	**0.00**
	1.00	**1.00**

Illustration of Data Standardization (z-score Normalization)

Salesman-ID	Total sales (Rs)	Score for sale
S001	-0.06	1.58
S002	-0.06	0.71
S003	-0.09	-1.02
S004	-1.12	-0.15
S005	0.51	0.28
S006	-0.45	1.58
S007	-0.29	1.58
S008	-0.80	-1.02
S009	0.65	-0.15
S010	2.46	-1.02
S011	1.42	-0.15
S012	-1.09	-0.59
S013	-0.91	-0.59
S014	-0.18	-1.02
μ :	**0.00**	**0.00**
σ :	**1.00**	**1.00**

23000.00	6.5

-0.08	0.93

Illustration of Data Standardization (z-score Normalization)

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	-0.06	1.58
S002	-0.06	0.71
S003	-0.09	-1.02
S004	-1.12	-0.15
S005	0.51	0.28
S006	-0.45	1.58
S007	-0.29	1.58
S008	-0.80	-1.02
S009	0.65	-0.15
S010	2.46	-1.02
S011	1.42	-0.15
S012	-1.09	-0.59
S013	-0.91	-0.59
S014	-0.18	-1.02
μ :	**0.00**	**0.00**
σ :	**1.00**	**1.00**

y_1	y_2
-0.08	0.93

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

$\text{ED1} = (-0.06 + 0.08)^2 + (1.58 - 0.93)^2$

ED1 = **0.42**

Illustration of Data Standardization (z-score Normalization)

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	-0.06	1.58
S002	-0.06	0.71
S003	-0.09	-1.02
S004	-1.12	-0.15
S005	0.51	0.28
S006	-0.45	1.58
S007	-0.29	1.58
S008	-0.80	-1.02
S009	0.65	-0.15
S010	2.46	-1.02
S011	1.42	-0.15
S012	-1.09	-0.59
S013	-0.91	-0.59
S014	-0.18	-1.02
μ :	**0.00**	**0.00**
σ :	**1.00**	**1.00**

y_1	y_2
-0.08	0.93

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(-0.06 + 0.08)^2 + (1.58 - 0.93)^2$

ED1 = **0.42**

ED2 = $(-0.06 + 0.08)^2 + (0.71 - 0.93)^2$

ED2 = **0.05**

Illustration of Data Standardization (z-score Normalization)

Salesman-ID	Total sales (Rs) x_1	Score for sale x_2
S001	-0.06	1.58
S002	-0.06	0.71
S003	-0.09	-1.02
S004	-1.12	-0.15
S005	0.51	0.28
S006	-0.45	1.58
S007	-0.29	1.58
S008	-0.80	-1.02
S009	0.65	-0.15
S010	2.46	-1.02
S011	1.42	-0.15
S012	-1.09	-0.59
S013	-0.91	-0.59
S014	-0.18	-1.02
μ :	**0.00**	**0.00**
σ :	**1.00**	**1.00**

y_1	y_2
-0.08	0.93

$$\text{Eucledin Distance (ED)} = \sum_{i=1}^{d} (x_i - y_i)^2$$

ED1 = $(-0.06 + 0.08)^2 + (1.58 - 0.93)^2$

ED1 = **0.42**

ED2 = $(-0.06 + 0.08)^2 + (0.71 - 0.93)^2$

ED2 = **0.05**

ED3 = $(-0.09 + 0.08)^2 + (-1.02 - 0.93)^2$

ED3 = **3.80**

Summary on Data Transformation

- Data transformation is useful of data modelling
- Normalization:
  - Each attribute is normalised by scaling its value so that they fall within a small specified range (for example 0.0 to 1.0)
  - Min-Max normalization
    - It is useful when data has varying ranges among attributes
- Standardization (z-score normalization):
  - The process of rescaling one or more attributes so that the transformed data have 0 mean and unit variance i.e. standard deviation of 1
  - Standardization assumes that data follows a Gaussian distribution
  - It is useful when the actual minimum and maximum of attribute are unknown