

Attribute normalization, standardization and dimension reduction of data

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1 a.

Table 1 Minimum and maximum attribute values before and after normalization

S. No.	Attribute	Before no	rmalization	After normalization		
		Minimum	Maximum	Minimum	Maximum	
1	pregs	0	13	5	12	
2	plas	44	199	5	12	
3	pres (in mm Hg)	38	106	5	12	
4	skin (in mm)	0	63	5	12	
5	test (in mu U/mL)	0	318	5	12	
6	BMI (in kg/m²)	18.2	50	5	12	
7	pedi	0.078	1.91	5	12	
8	Age (in years)	21	66	5	12	

Inferences:

- 1. Due to outliers our analysis of data can be very poor and it can violate our assumptions.
- 2. From our analysis the mean is more affected by outliers so we replaced outliers by median.
- 3. Before normalization, the attribute having bigger values will make no importance of smaller value attribute.

So, the analysis will be more partial. Now after normalization, each value is now between 5 to 12, so they will have equal importance in the analysis.



Attribute normalization, standardization and dimension reduction of data

b.

Table 2 Mean and standard deviation before and after standardization

S. No.	Attribute	Before stan	dardization	After standardization			
		Mean	Std. Deviation	Mean	Std. Deviation		
1	pregs	3.783	3.271	0	1		
2	plas	121.656	30.438	0	1		
3	pres (in mm Hg)	72.127	11.147	0	1		
4	skin (in mm)	20.438	15.699	0	1		
5	test (in mu U/mL)	60.919	77.636	0	1		
6	BMI (in kg/m ²)	32.199	6.411	0	1		
7	pedi	0.428	0.245	0	1		
8	Age (in years)	32.76	11.055	0	1		

Inference

1. Before standardization, the attribute having bigger values will make no importance of smaller value attribute. So, the analysis will be more partial. Now after standardization, every value has a common mean of 0 with variance 1. so there is not much variation in analysis.

a.

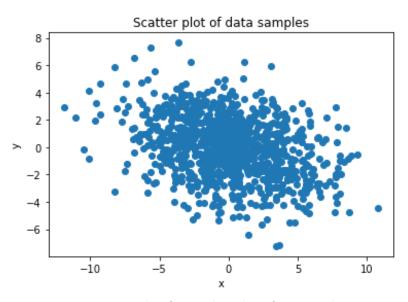


Figure 1 Scatter plot of 2D synthetic data of 1000 samples



Attribute normalization, standardization and dimension reduction of data

Inferences:

- 1. Attribute 2 is negatively related to the Attribute 1 according to the graph. The covariance will be negative.
- 2. Seeing the density of the graph, the distribution of both the attributes seems to be symmetric. The mean of both the attribute is approximately 0..

b.



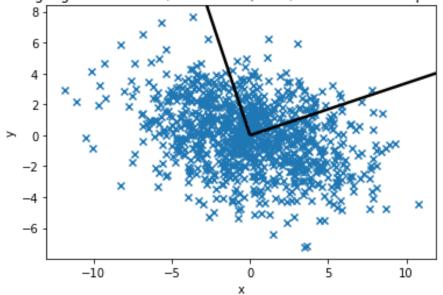


Figure 2 Plot of 2D synthetic data and Eigen directions

Inferences:

- 1. The spread along the first eigen vector (Eigen value=4) is not much as compared to the spread along the second eigen vector (Eigen Value=14). The data is more of a kind spread in a linear fashion with a smaller portion in the other vector's direction.
- 2. The density of points near the intersection of axis is very dense, and it gradually decreases as the spread increases. In other word, the number of points decreases as move far from the center.



Attribute normalization, standardization and dimension reduction of data

c.

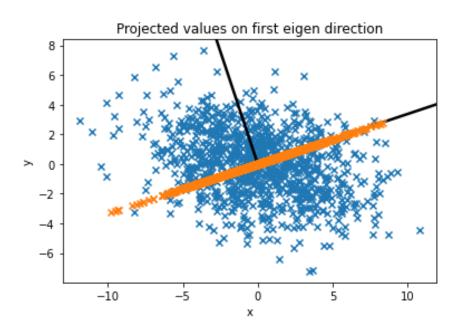


Figure 3 Projected Eigen directions onto the scatter plot with 1st Eigen direction highlighted

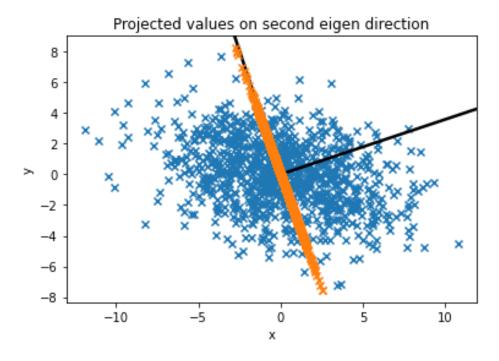


Figure 4 Projected Eigen directions onto the scatter plot with 2nd Eigen direction highlighted



Attribute normalization, standardization and dimension reduction of data

Inferences:

- 1. The Eigen Value(=12) which is greater has more spread of data along its respective Eigen direction while the Eigen Value(=4) has less spread along its respective Eigen direction.
- 2. Regarding the density, along the first Eigen vector (smaller line), the variance is not very large, so the spread is not so much varying. However, along the second Eigen Vector, the variance is high, so the spread is more, so the density actually is high near the intersection and spread is large.
- **d.** Reconstruction error = 2.710

Inferences:

1. larger the reconstruction error, more loss in the nature of data. So, the reconstruction error must very less. Here the reconstruction error was very small so we can consider it as 0 because the number of dimension remained is equal to the after reconstructing the data.

3.a.

Table 3 Variance and Eigenvalues of the projected data along the two directions

Direction	Variance	Eigenvalue
1	1.992	1.853
2	1.992	1.853

Inferences:1. Higher the values of Eigen Vector, more variance along that vector, so more strength along that direction. So, we can say that data will be more spread along the first Eigen vector.



Attribute normalization, standardization and dimension reduction of data

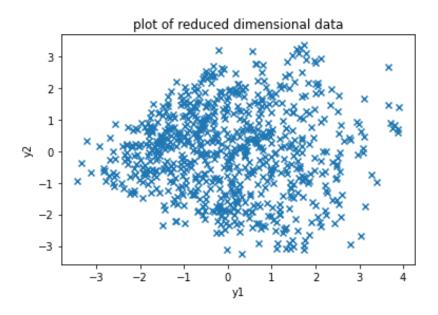


Figure 5 Plot of data after dimensionality reduction

Inferences:

1. As the density of data along positive slope is more so by seeing the graph the data is positively correlated.

b.

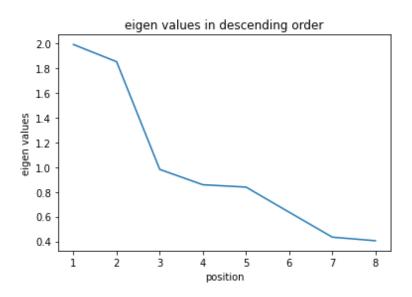


Figure 6 Plot of Eigenvalues in descending order



Attribute normalization, standardization and dimension reduction of data

Inferences:

- 1. It drops rapidly from second to third Eigen value and then decreases gradually.
- 2. From the third Eigenvalue the rate of decrease changes substantially.

c.

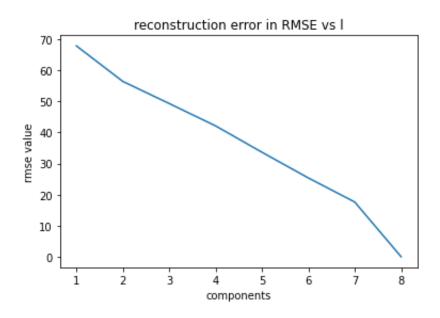


Figure 7 Line plot to demonstrate reconstruction error vs. components

Inferences:

1. More the magnitude of reconstruction error, lesser the quality of reconstructions. As we can see the RMSE increases, as we keep dropping the dimensions At I = d = 8, the reconstruction error is almost zero.



Attribute normalization, standardization and dimension reduction of data

Table 4 Covariance matrix for dimensionally reduced data (I=2)

	x1	x2
x1	1.992	0
x2	0	1.853

Table 5 Covariance matrix for dimensionally reduced data (I=3)

	x1	x2	х3
x1	1.992	0	0
x2	0	1.853	0
х3	0	0	0.982

Table 6 Covariance matrix for dimensionally reduced data (I=4)

	x1	x2	х3	x4
x1	1.992	0	0	0
x2	0	1.853	0	0
х3	0	0	0.982	0
x4	0	0	0	0.858

Table 7 Covariance matrix for dimensionally reduced data (I=5)

	x1	x2	х3	x4	x5
x1	1.992	0	0	0	0
x2	0	1.853	0	0	0
х3	0	0	0.982	0	0
x4	0	0	0	0.858	0
x5	0	0	0	0	0.839

Table 8 Covariance matrix for dimensionally reduced data (I=6)

	x1	x2	х3	x4	x5	x6
x1	1.992	0	0	0	0	0
x2	0	1.853	0	0	0	0
х3	0	0	0.982	0	0	0
х4	0	0	0	0.858	0	0
x5	0	0	0	0	0.839	0
x6	0	0	0	0	0	0.636



Attribute normalization, standardization and dimension reduction of data

x1 x2 х3 х5 х6 х7 х4 1.992 0 х1 0 0 0 0 0 1.853 0 0 0 0 0 х2 0

Table 9 Covariance matrix for dimensionally reduced data (I=7)

0.982 0 0 0 0 0 0 х3 х4 0 0 0 0.858 0 0 0 х5 0 0 0 0 0.839 0 0 х6 0 0 0 0 0 0.636 0 0 0 0 0 0 0.434 x7 0

Table 10 Covariance matrix for dimensionally reduced data (I=8)

	x1	x2	х3	x4	x5	x6	x7	x8
x1	1.992	0	0	0	0	0	0	0
x2	0	1.853	0	0	0	0	0	0
х3	0	0	0.982	0	0	0	0	0
x4	0	0	0	0.858	0	0	0	0
x5	0	0	0	0	0.839	0	0	0
х6	0	0	0	0	0	0.636	0	0
x7	0	0	0	0	0	0	0.434	0
х8	0	0	0	0	0	0	0	0.405

Inferences:

- 1. As we chose to reduce the dimensionality ,so while reconstructing the data we lost those dimensions that we chose to discard so the off diagonal elements are zero means not correlated.
- 2. The diagonal elements are variances and off diagonal elements are zero we chose the Eigen vectors to project data on so the maximum variance is only along Eigen vectors(diagonal elements) and there is almost no covariance along the direction of other vectors.
- 3. The diagonal values keep decreasing as we move from left to right.



Attribute normalization, standardization and dimension reduction of data

- 4. This is because we took the I strongest Eigen vectors(highest Eigen values) so the trend is decreasing.
- 5. From the magnitude of diagonal elements, the first component captures data variations the best.
- 6. From the value of diagonal elements, the seventh and eighth components shall give the optimum reconstruction along with dimensionality reduction.
- 7. The magnitude of the 1st diagonal element (topmost left corner) in each of the obtained covariance matrices is same as we took the I strongest vectors so for each value of I ranging from 2 to 8 the strongest Eigen vector i.e. highest Eigen value remains the same.
- 8. The magnitude of the 2nd diagonal element (topmost left corner) in each of the obtained covariance matrices is same as we took the I strongest vectors so for each value of I ranging from 2 to 8 the second strongest Eigen vector i.e. second highest Eigen value remains the same.
- 9. The 3rd, 4th, 5th, 6th, and 7th diagonal elements(if present) across covariance matrices are same because we chose I strongest vectors to project data on so the value and order always remains same and in the covariance matrixes where there isn't any 3rd, 4th, 5th, 6th or 7th diagonal present is because we took dimension less than 3, 4, 5, 6 or 7 respectively

d.

Table 11 Covariance matrix for original data

	pregs	plas	pres	skin	test	BMI	pedi	Age
pregs	1	0.118	0.209	-0.097	-0.108	0.028	0.005	0.561
plas	0.118	1	0.205	0.060	0.180	0.228	0.082	0.274
pres (in mm Hg)	0.209	0.205	1	0.026	-0.051	0.272	0.022	0.326
skin (in mm)	-0.097	0.06	0.026	1	0.473	0.374	0.153	-0.101
test (in mu U/mL)	-0.108	0.180	-0.051	0.473	1	0.172	0.199	-0.074
BMI (in kg/m ²)	0.028	0.228	0.272	0.374	0.172	1	0.124	0.078
pedi	0.005	0.082	0.022	0.153	0.199	0.124	1	0.036
Age (in years)	0.561	0.274	0.326	-0.101	-0.074	0.078	0.036	1

Inferences:

1. The off-diagonal values in original matrix are close to zero but not that close to zero so as to treat them negligible but in the covariance matrix obtained after PCA I=8 reduction the off diagonal values are pretty close to zero that we considered them to be zero.



Attribute normalization, standardization and dimension reduction of data

- 2. The magnitude of diagonal elements in original covariance matrix is one while in the covariance matrix obtained after PCA I=8 reduction the diagonal values are not one and in fact less in magnitude than that of original covariance matrix.
- 3. No there isn't any trade of decrease in diagonal elements like covariance obtained after dimensionality reduction in fact in original matrix all diagonal values are equal.