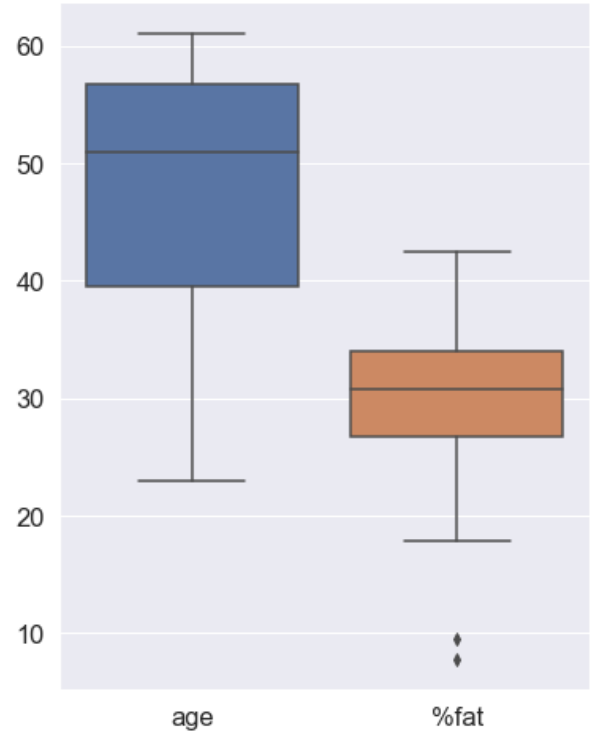
2.4 (a)

	age	%fat
Mean	46.444444	28.783333
Standard Deviation	13.218624	9.254395
Median	51.000000	30.700000

2.4(b)



2.4 (c)

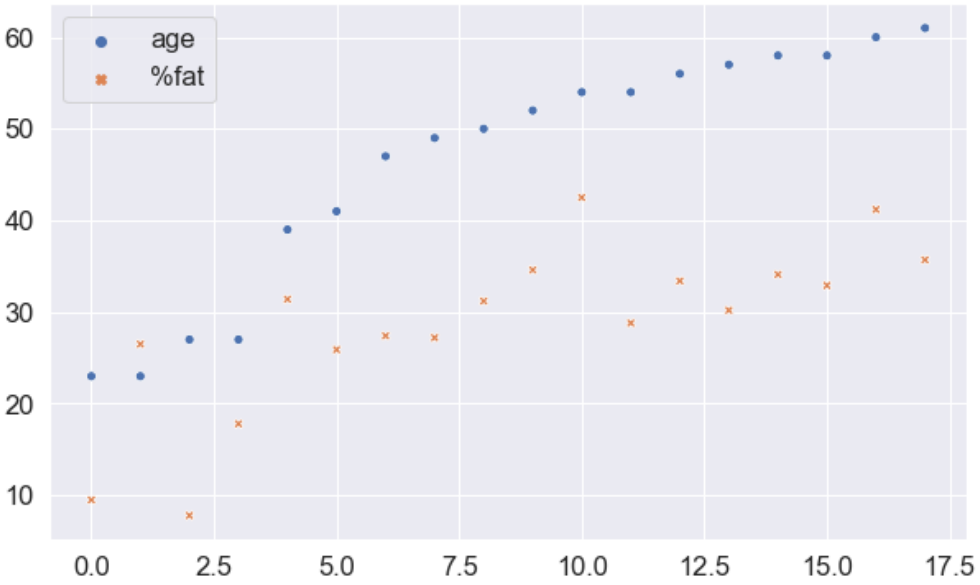


Fig: scatter plot

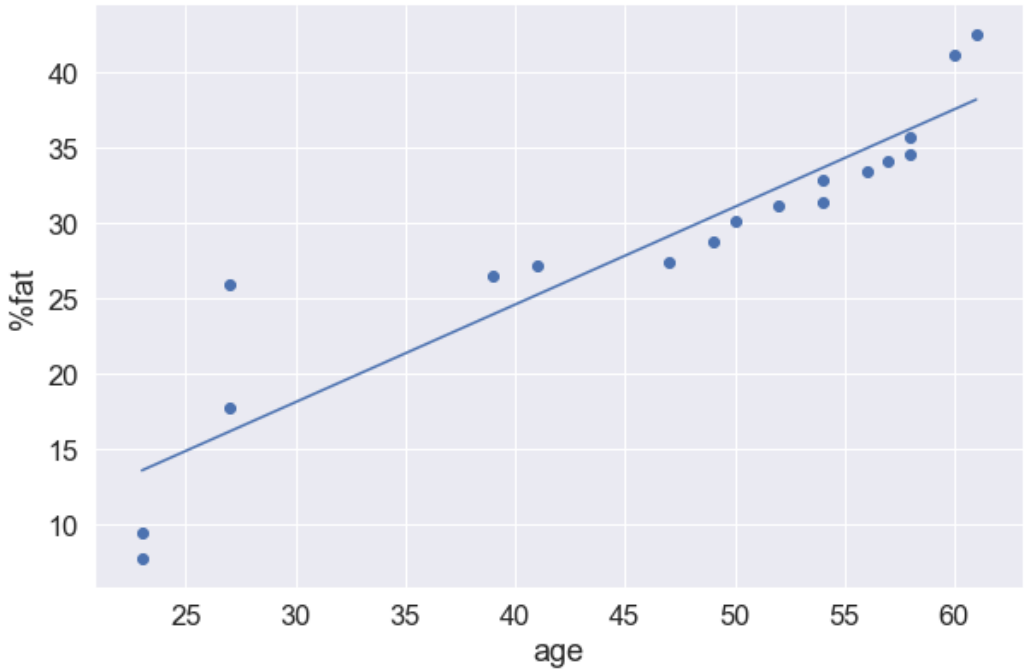


fig: qq-plot

2.8 (a)

Implemented 4 similarity algorithms. Compared with Cosine similarity from Scikit Learn and Scipy. There are some differences between 3 Cosine implementations. It might happen due to internal normalization and decimal precision.

	A1	A2	Euclidean	Manhattan	Supremum	Cosine	Cosine-Scikit	Cosine-Scipy
x1	1.5	1.7	1	1	1	1	1	1
x2	2.0	1.9	5	5	4	2	3	4
x3	1.6	1.8	3	3	3	4	4	2
x4	1.2	1.5	2	2	2	5	2	3
x5	1.5	1.0	4	4	4	3	5	5

2.8 (b) – used L2 norm

	A1	A2	A1norm	A2norm	Euclidean
x1	1.5	1.7	0.661622	0.749838	1
x2	2.0	1.9	0.724999	0.688749	4
x3	1.6	1.8	0.664364	0.747409	2
x4	1.2	1.5	0.624695	0.780869	3
x5	1.5	1.0	0.832050	0.554700	5

3.7 (a)

(35 – 13) / (70 – 13) = **0.38596491228070173**

3.7 (b)

0.38926097658709724

3.7 (c)

0.35

3.7 (d)

I would use min-max normalization if there is no additional data which can change min or max. This is because to use z-score or decimal methods, we need to save extra parameters for future data and for reconstruction of original data. But if the min-max cannot be guaranteed, I would use the decimal method here, because the distribution of this small sample may not reflect the actual distribution of data, and hence, statistics of the sample might be wrong.

3.9 (a)

[5, 10, 11, 13],

[15, 35, 50, 55],

[72, 92, 204, 215]

3.9 (b)

[5, 10, 11, 13, 15, 35, 50, 55. 72],

[92],

[204, 215]

3.9 (c)

Using KMeans clustering

[5, 10, 11, 13, 15, 35],

[50, 55, 72, 92],

[204, 215]