Journal of Physical Education and Sport ® (JPES), 17(4), Art 300, pp. 2622 - 2631, 2017
online ISSN: 2247 - 806X; p-ISSN: 2247 – 8051; ISSN - L = 2247 - 8051 © JPES

Original Article

Physical fitness assessment using supervised SOM classification based on BMI of college students, northern China

FEI WANG[1], HAIXIA FU[2]
[1,2]School of Physical Education, Shanxi University, CHINA

Published online: December 30, 2017
(Accepted for publication December 15, 2017
DOI:10.7752/jpes.2017.04300

Abstract:
The physical fitness of college students in northern China, was systermetic evaluated with classified data by supervised SOM , then differences of classified data were validated with ANOVA. The relative importance of all physique indicators in each classified data were evaluated by PCA. BMI was considered as the supervised parameter in SOM analysis due to the reasonable and prevalent parameter reflecting health of physical health. The results were as follows: (1) The supervised SOM provided the intuitive and visual characteristics of classification for physical fitness data as well as the emphasis on BMI; (2) The differences of the classifications coupled with emphasized BMI were validated by ANOVA, and the relative importance indicators were pointed by PCA for each classification. Physique indicator showed heterogeneity in different classifications. Height and Pulup were relative important for male students, but Weight for female students; (3) the methods presented here were universally applicable, and the better performance could be promoted with much more data inputs. The results and the relevant methods of the study are valuable for deepening our understanding of BMI effects on physical fitness and can be used to develop a practical strategy for effective physical activities.
Key Words: Physical finess; physique indicator; supervised SOM; BMI; PCA

Introduction

Adolesent obesity and its associated risks have been lised as parts of national strategy by the government as one of the biggest threats to public health in China (Gu et al., 2005; Tian et al., 2016; Wang, Mi, Shan, Wang, & Ge, 2007). Overweight and obesity are defined as abnormal or excessive fat accumulation that may impair health (P. S. Collaboration, 2009). Being overweight or obese is associated with an increased risk for a number of common causes of disease and death including diabetes, cardiovascular disease and some cancers (B. P. L. T. T. Collaboration, 2015; G. B. M. Collaboration, 2016; Flegal, Kit, Orpana, & Graubard, 2013). These problems continue to provoke national and international concerns. Meanwhile, there is considerable evidence linking obesity with lots of long-term and immediate physiological health risks which highlights the importance of revealing early overweight and obesity (Roswall et al., 2017). Especially for childhood and adolescent, the obesity can persist into adulthood to induce the direct severe health risks. The previous researches have revealed that approximaltly up to 50% of obese adolescents remain obese in adulthood (Calle, Rodriguez, Walker-Thurmond, & Thun, 2003; Flegal et al., 2013; Krause, Ware, McPherson, Lennox, & O’Callaghan, 2016). In addition to the increased potential risks for health problems, adolescents still face immediate health consequences due to obesity, including hyperlipidemia (Rao et al., 2016), hypertension (Singh, Pandey, & Rani, 2017) and other physiological and psychological problems (Crews, Schneider, Yalla, Reeves, & Vileikyte, 2016). In addition, previous researches have shown high levels of dissatisfaction with body size and shape amongst femal colledge students, as well as a desire to be thinner with trend of more prevalent among girls (Joseph et al., 2016; Moussally, Brosch, & Van der Linden, 2016), and other psychological issues of low self esteem, depression, et al (Crews et al., 2016).

For individuals, the risk of poor health increases sharply with increasing BMI (Calle et al., 2003; Roswall et al., 2017). BMI has been shown the high correlation with adiposity in both adults (Tian et al., 2016) and children (Kabisch, van den Bosch, & Lafortezza, 2017), and it is reasonable indicator in measure of overweight and obesity which has been used to evaluate the physical fitness health for long time. BMI is also used to produce the trends, estimates and other overweight porblem (Finucane et al., 2011). Dolton and Xiao (2015) investigated the relationship of BMI intergenerational transmission in China, and the results from He et al. (2015) indicated the lower BMI cutoffs is suitable to to define overweight and obesity in China. BMI has been the most appropriate indicator in the classification of physical fitness with emphasis on obesity issues. For college students, regular physical activity has been certificated contributes to good health (Pellicer-Chenoll et al., 2015). The good physical state is always associated to many physical activities, as well as preventing diseases such as obesity, diabetes and hypertension et al. In addition the increase of moderate physical activity for college students has a positive effect on mental and physical health which enhances opportunities to improve academic performance. In China, the physical fitness test for all

Corresponding Author: FEI WANG, E-mail: nemochina2008@hotmail.com

students from primary school to university has been implemented for many year, and public physical fitness has been promoted as national strategy by the government.

This study selected 6531college students (2366 samples for male and 4165 samples for female) in northern China as the a random sample. The total nine physique indicators for both male and femal students were employed to evaluate the physical fitness of college students. The supervised SOM (self organization map) based on BMI indicator was used to classify the data into 6 clusters for both male and female students. The 6 clusters of data based on SOM were validated by ANOVA, as well as the comparisions of eight indicators (except BMI). The relative importance of indicators in each cluster category for both male and female students was conducted by PCA (Principle component analysis). Our main objectives were: (1) to elaborate the intuitive and visual characteristics of classification using supervised SOM for multidimensional datad with huge samples; (2) to identify and validate the differences of classified data as well as the relative importance of physique indicators in each classified physique category; and (3) to propose a new perspective for evaluation of physical fitness with emphasis on BMI and future prediction in big data of public physical fitness.

Material & methods

Physique indicators

The tests of physique indicators of college students in northern China were strictly followed National Physical Fitness Standard for students (revised in 2014) by Department of Physical, Health and Arts Education, Ministry of Education of the people's republic of China (MOE) (http://www.moe.edu.cn/s78/A17/twys_left /moe_943/moe_947/201407/t20140721_172364.html). The test was implemented every year for all students from primary school to university. All testing instruments were specially equipped with the Guide by MOE. For college students, the revelent physique indcators are introduced as follows:

1) Height (abbre. Height), measured without wearing shoes, instrument error is limited less than 0.1 cm, the testing error is less than 0.5 cm.
2)Weight (abbre. Weight), measured without wearing shoes, instrument error is limited less than 0.1% (less than 0.1 kg /100kg), the testing error is less than 0. 0.1 kg.
3) lung's capacity/vital capacity (abbre. Lung): measured three times with intervals of not less than10s and record the maximum, unit: mL.
4) 50 meter straight race (abbre. X50m): measured in straight track, instrument of timer error is limited less than 0.2 s/minute, the record should be accurate to the decimal point one.
5) Standing long jump (abbre. Jump): measured three times and record the maximum, unit: cm.
6) 800 meter race for female (abbre. X800m) / 1000 meter race for male (abbre. X1000m): measured in field track, instrument of timer error is limited less than 0.2 s/miniute, the record should be accurate to the integer.
7) situp in 1minute for female (abbre.Xlmin_sit): measured following the Standared, record the numbers in 1 minute.
8) pull-ups for male (abbre. Pullup): measured following the Standared, record the numbers in 1 minute.
9) sit-and-reach (abbre. Bend): measured twice and record the best, and record should be accurate to the decimal point one, unit: cm.
10) BMI: body mass index, defined as the body mass divided by the square of the body height, and is expressed in units of kg/m2, resulting from mass in kilograms and height in metres.

Datasets collection

The deatesets included the above physique indicators were collected with the approval of the competent department of education administration in northern China. Indicators depicted from the datasets were measured for sophomores in 2014. The total of 6531 samples (2366 samples for male and 4165 samples for female) were employed in the study. The basic summary of dataset was shown in Table 1.

Table 1 Descriptive summary of physique indicators of college students

	indicator	n	Height (cm)	Weight (kg)	BMI	Lung (mL)	X50m (s)	Jump (cm)	Bend (cm)	X800m/ X1000m(s)	X1min_sit/ Pullup(n)
male	max	2366	193.0	124.4	37.93	9999	14.60	315.00	40.00	472.00	23
	min		150.5	41.0	14.36	1047	5.10	77.00	-20.00	193.00	1
	mode		170.4	64.4	17.84	4012	7.30	227.00	0.00	276.00	1
	mean		172.1	65.6	22.13	4070	7.60	222.09	12.49	273.96	5
	sd		5.8	11.6	3.64	771	0.81	21.86	8.18	36.99	4
female	max	4165	185.4	96.3	36.89	9171	16.90	314.00	38.70	448.00	93
	min		141.4	34.9	13.34	616	6.10	73.00	-20.00	190.00	1
	mode		160.0	50.3	20.37	2508	9.40	154.00	0.00	253.00	30
	mean		159.6	52.9	20.77	2655	9.71	161.89	16.00	267.92	32
	sd		5.4	7.4	2.68	557	1.05	18.40	7.50	30.64	8

Study design

The datasets was divided into male part and female part. For each part, the classification was conducted using supervised SOM (details see statistical method section). The BMI indicatior was used as the supervised

parameter. In the processes of supervised SOM, the optimal cluster number and SOM mapping segmentations were confirmed by Within-Cluster Sum of Squares (WCSS) and K-mean Matrix, respectively. The classified dataset were then used to indentify the differences of classified group by ANOVA. The relative importance of physique indicators in each classiflied group was determined using Principle component analysis (PCA). The basic processes of the study are as follows.
Step1: Male data and female data are extracted for the whole dataset, respectively.
Step2: Setting parameters and supervised indicator, to execute SOM analysis and determine the final classifications.
Step3: indentify the differences of classified groups using ANOVA analysis.
Step4: indentify the relative important indicators for each classified groups using PCA method.
Step5: summaries and conclusion, if possible prediction using SOM in future.

Statistical methods
SOM is a particular type neural network, which is applied according to Kohonen to ordinate, cluster and map data (Kohonen, 1998).The SOM indicates the neurons of superised ANN (artificial neuron network) learn to distinguish between similar and dissimilar features of the normalized input data, which can be mapped as clustered inputs. The term supervised in this context means the learning algorithm is guided by the known output patterns and learns the patterns from features of the inputs (here is BMI datasets). The way in which SOM can be utilized for classification of the research is to cluster the weight vector into different classes using the information of map structure, e.g., the U-matrix after the clustering process (Cuss & Guéguen, 2016; Park, Chon, Bae, Kim, & Lek, 2018).
This study utilized the supervised SOM method in combination with the clustering techniques described U-matrix method and K-means method by calculating the Euclidian distances of data features for the classification. The processes are as following.
Step1: the physique data are classified into two-dimensional units (20 □20) through the training of the SOM with BMI dataset (Fig. 3 showed the training progress of SOM in for male and female college students);
Step2: all data patterns are divided into clusters using the clustering techniques of the U-matrix method;
Step3: the K-means method are used to visualize and better understand the features of the data;
Step4: U-matrix map visualized the relative distances between neighboring data with light areas representing neighboring data of smallest distances belonging to a cluster, and the black colors representing the biggest distances between neighboring data and denote borders between clusters;
Step5: K-means algorithm partitions the input data space into a specified number of clusters based on the U-matrix (Fig. 4 showed the optimal classification numbers of WCSS);
Step6: The corresponding partitioned map (SOM mapping, Fig. 5 showed the SOM maping with optimal classification numbers for male and female college students)
Step7: The SOM mapping displays the distribution of individual paramters (Fig. 6)
Step8: The trained SOM strucutres could be used for prediction (omitted in the research).
A more complete descriptions of of supervised SOM can be found in the book by Kohonen (2012). In this study, all SOM analyses were performed using the “kohonen” package in R language(http://cran.R-project.org/).
To evaluate the differences of classified groups based on supervised SOM are systematically analyzed by oneway ANOVA, and the multiple comparisons are also conducted with base level (mean levels, avoiding more pairwise comparisons) using the t-test. All analysis were made in R (http://cran.R-project.org/).
The PCA was used to investigate the relative important indicators for both male and female college students to identify the major physique indicators influencing their physical fitness. The “prcomp” function in R core packages was used for the PCA. In addition, the suitability of the PCA was tested and confirmed by performing the matrix of cumulative variance contribution to confirm the suitable of PCA analyzing for our data. In the research, the “biplot” was used to produce the visualised loading diagram of PCA rresult, as well as 95% individuals delineated with ellipse. All PCA analysis was performed by R (http://cran.R-project.org/).
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Results
Descriptive Statistics
Table 1 shows the descriptive summary of physique indicators of college students. The results show BMI ranges from 14.36 to 37.93 in male students and from 13.34 to 36.89 in female students. The differences between mode vales and mean values for each indicator are relatively small. The result shows the relative slight advantage in male students than that in female students. However, the Pullup parameter in male shows dismal record with the mean value of 5. The best record in each indicator shows significant advantage than the worst record for both male and female students.
The data distribution of each indictor was shown in Fig.1 (male students) and Fig.2 (female students). Most parameters show normal or approximate normal distribution except the Pullup parameter in male showing severe skewness.

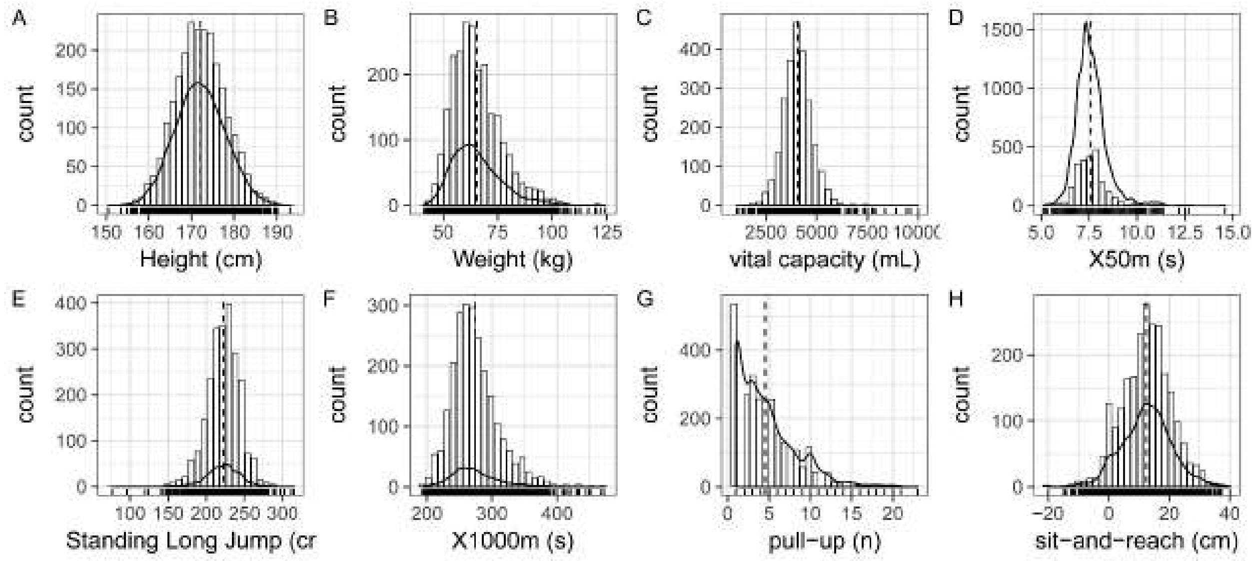

Fig.1 Data distribution in male college students

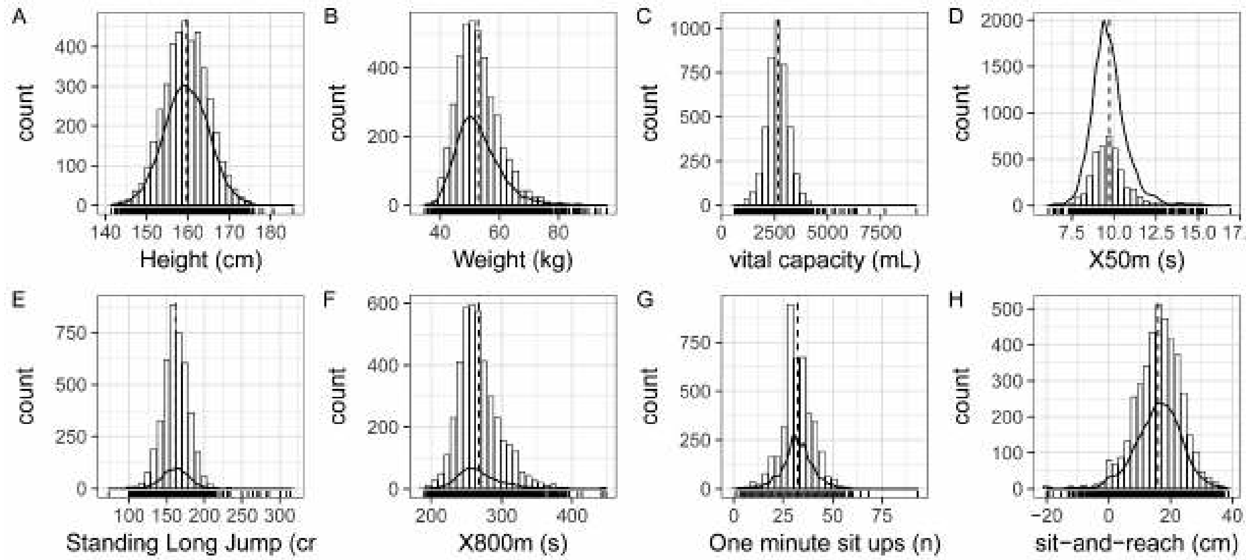

Fig.2 Data distribution in female college students

Classification by SOM

The network of SOM has a rectangular shape with a size of 20×20 neurons in height and width, respectively. The neurons' shape is hexagonal, such that each neuron has 6 neighbouring neurons. After determining the size and shape of the lattice, a value is assigned for each input variable to each of the nodes or neurons with initialized data. In the training phase, each neuron of the grid competes to win each of the input vectors of the sample. The winner neuron exhibites the minor

Euclidean distance between its weight vector and the input vector. In SOM training progress the mean distance to closest unit shows gradually decrease with the increase of interations in both male dataset (Fig. 3a) and female dataset (Fig. 3b). When the iteration reaches 100, the mean distance to closest uint is too small to meet SOM requirements. The more larger iterations do not increase precision but occupying the computing time remarkably.

The optimal classification numbers can be determined with the help of WCSS after the operation of K-means algorithm partitions based on the U-matrix (Fig. 4). Figure 4 indicates the optimal number of clusters is 6 for both male and female due to the extreme variation trend at the point.

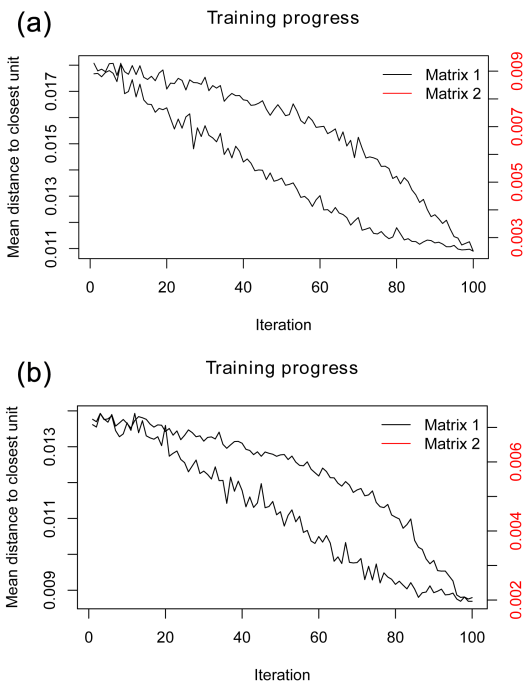

Fig.3 Training progress of SOM in (a) male and (b) female college students

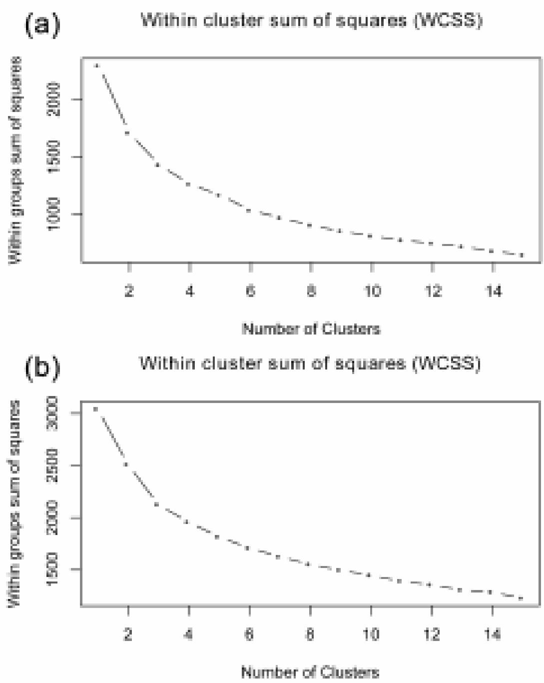

Fig.4 Optimal classificationn umbers of WCSS in (a) male and (b) female college students

SOM mapping in Fig.5 shows the corresponding partitions based on K-means algorithm and the U-matrix partition. The component SOM mappings of the recorded variables are shown in Fig. 6. As shown Fig. 6, it intuitively depicts the variations of each indicator on the classified two-dimensional plane according to the classifications in Fig. 5. The cluster 1 and cluster 2 on SOM mapping in male, show relative non-colours (relative high value) in indicators of Height, Jump, Lung and Bend (Fig. 6a). The colours do not represent any subject, and the associated value is merely an approximation. This displaying form gives an idea of the values achieved by the subjects placed in a given neuron in each analyzed variable separately. Similarly, the cluster 4 is prone to dispalying the relative higher values of X800m, X50m, Xlmin_sit, Bent (Fig. 6b). SOM mapping gengerally provides the intuitional visiual describes for each indicator.

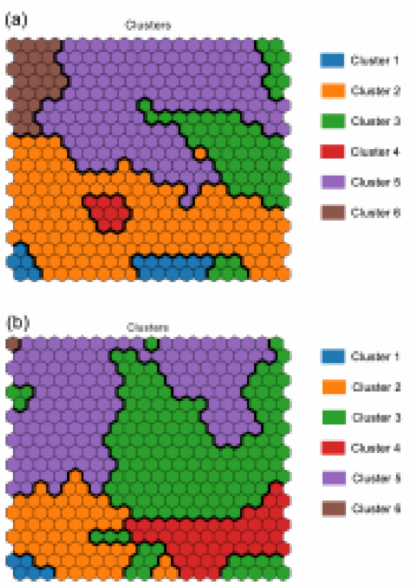

Fig. 5 SOM maping with optimal classification numbers for (a) male and (b) female college students

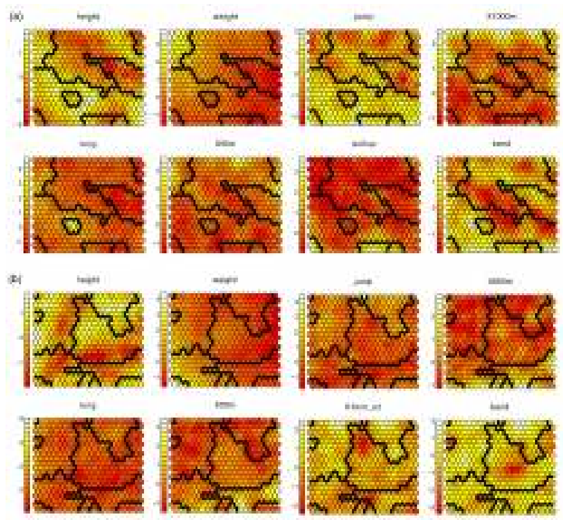

Fig. 6 SOM maping in each parameter for (a) male and (b) female college students

The descriptive summary of 6 clustered data from SOM is shown in Table 2. Cluster 2 in male categories and Cluster 3 in female categories contain the largest number of samples, respectively. Cluster 1 and Cluster 6 in female contain the relative the minimum number of samples showing only 47 samples and 11 samples, respectively. Similarly, Cluster 3 in male categories shows the minimum number of samples. BMI indicators in both male and female show partially overlaping in the classified categories. These typical characteristcs are useful information in following analysis.

Table 2 Descriptive summary of physique indicators with different clusters by SOM

cluster	n	male										female									
		indicator	Height	Weight	BMI	Lung	X50m	Jump	X1000m	Pull-up	Bend	n	Height	Weight	BMI	Lung	X50m	Jump	X800m	X1min_sit	Bend
cluster 1	96	max	182.9	70.2	23.9	5574	8.1	271.0	308.0	23	34	47	168.5	96.3	36.9	3873	15.5	194.0	414.0	50	26
		min	159.3	46.6	17.5	2278	5.5	207.0	193.0	8	5		144.1	63.0	27.7	1702	8.0	108.0	249.0	11	0
		mode	173.6	51.3	18.8	3601	6.9	259.0	229.0	12	23		163.8	66.2	29.5	2890	11.0	143.0	342.0	29	10
		mean	169.4	58.5	20.4	3864	6.9	241.4	241.9	14	17		159.3	79.5	31.3	2785	10.8	147.1	308.1	28	14
		sd	5.1	5.5	1.5	592	0.4	14.9	22.6	3	6		5.6	8.4	2.4	536	1.3	18.4	34.7	8	6
cluster 2	889	max	193.0	88.5	27.1	7794	9.0	315.0	384.0	16	40	570	180.7	86.3	29.5	4820	15.1	314.0	443.0	55	33
		min	159.1	46.7	14.8	1886	5.1	170.0	197.0	1	-20		143.9	49.3	21.1	910	6.4	100.0	213.0	5	-20
		mode	174.8	60.0	18.6	4012	7.3	243.0	248.0	5	0		163.8	60.6	23.0	2709	9.5	154.0	268.0	30	14
		mean	175.2	63.9	20.8	4309	7.3	234.8	259.7	5	14		158.4	62.2	24.8	2722	10.1	156.7	281.3	30	16
		sd	5.2	8.5	2.5	624	0.6	16.7	26.7	3	9		5.4	6.1	1.8	481	1.0	18.7	33.4	7	7
cluster 3	361	max	184.4	70.1	24.3	4808	11.3	256.0	433.0	19	32	1639	177.3	65.8	24.4	3983	12.6	314.0	374.0	56	32
		min	150.5	41.0	14.4	1047	6.2	77.0	204.0	1	-10		141.4	35.8	13.3	616	6.4	73.0	193.0	1	-20
		mode	168.2	50.3	20.6	3463	7.6	227.0	248.0	1	0		157.7	46.9	19.7	2508	9.4	154.0	257.0	30	0
		mean	167.1	53.7	19.3	3359	7.8	210.0	278.3	5	12		159.1	49.9	19.7	2465	9.7	158.4	265.9	30	13
		sd	4.8	4.9	1.9	561	0.6	19.8	33.4	3	7		5.3	5.4	1.7	480	0.8	17.5	25.1	7	8
cluster 4	30	max	185.0	77.0	24.6	9999	8.6	275.0	346.0	13	31	454	185.4	62.4	23.5	4004	16.9	225.0	448.0	55	36
		min	161.3	52.8	18.1	5076	6.6	190.0	227.0	1	4		143.8	37.0	16.0	775	8.2	100.0	234.0	1	-11
		mode	175.2	59.5	-	-	8.0	228.0	276.0	4	12		159.4	48.0	17.8	2735	10.7	150.0	266.0	30	20
		mean	174.3	64.6	21.3	6571	7.5	224.5	285.7	5	16		157.2	49.1	19.9	2517	11.0	150.4	297.5	30	16
		sd	5.4	4.9	1.5	1385	0.5	17.4	29.7	3	7		4.7	4.1	1.5	447	1.2	16.3	35.6	9	7
cluster 5	835	max	184.6	91.3	30.9	5642	12.7	276.0	468.0	12	37	1444	185.4	73.6	25.1	5330	12.1	308.0	396.0	93	39
		min	153.5	50.2	17.3	1183	5.6	120.0	197.0	1	-20		147.0	34.9	15.5	1046	6.1	100.0	190.0	3	-4
		mode	172.8	63.3	20.8	3461	7.8	215.0	276.0	1	0		162.1	52.0	19.6	3899	9.0	167.0	245.0	35	16
		mean	170.6	68.2	23.5	3961	7.8	213.8	282.9	3	11		161.4	53.0	20.3	2853	9.1	172.0	254.2	36	19
		sd	4.8	7.5	2.6	553	0.9	19.4	37.2	2	8		5.1	5.7	1.9	511	0.7	14.8	22.8	7	7
cluster 6	155	max	189.7	124.4	37.9	8362	14.6	288.0	472.0	12	29	11	166.4	59.3	22.5	9171	9.9	208.0	369.0	46	29
		min	160.4	74.3	25.0	2324	6.0	146.0	217.0	1	-12		153.3	42.5	18.1	5218	7.8	135.0	239.0	15	10
		mode	181.8	85.5	27.8	4006	8.1	214.0	276.0	1	0		-	-	-	-	9.9	177.0	-	35	-
		mean	174.7	93.0	30.5	4584	8.2	209.3	315.5	2	10		160.2	51.8	20.2	6497	9.1	173.2	279.8	31	18
		sd	5.5	8.8	2.7	905	1.2	23.0	47.6	2	7		4.3	4.6	1.3	1109	0.7	18.8	39.7	9	7

Differences of Classified Data using ANOVA

The differences of classified six cluser categories are captured by ANOVA in each indicator analysis (Fig. 7 and Fig.8). The ANOVA results of both male and female reveal the significant differences with the camparisions to the base level in cluster categories ($p<0.001$). Obviously, Cluster 4 (the less samples) in male categories shows less number of significant differences in camparisions with base level especially in Weight, X50m, Jump, X800m, Pullup and Bend indicators. However, it shows extremely significant difference ($p<0.001$) to base level in Vital capacity in Cluster 4 , as well as the relative the highest mean values (Fig. 7C). In addition, Cluster 3 displays no significant difference to base level in Bend ($p>0.05$) but significant in Cluster 4 ($p<0.05$) (Fig. 7H). In female categories, the Cluster 6 (the less samples) is prone to showing the less number of significant differences in camparisions with base level (Fig. 8). However, Cluster 4 shows extremely significant difference ($p<0.001$) in Vital capacity and significant differences ($p<0.05$) in X50m and Jump, respectively (Figs. 8C, 8D, 8E). In addition, the resluts also show no signiciant differences ($p>0.05$) to the base level in Cluster 1 for Height and Lung (Figs. 8A, 8C), Cluster 5 for Weight (Figs. 8B), and Cluster 1, 2, 4 for Bend (Figs. 8H).

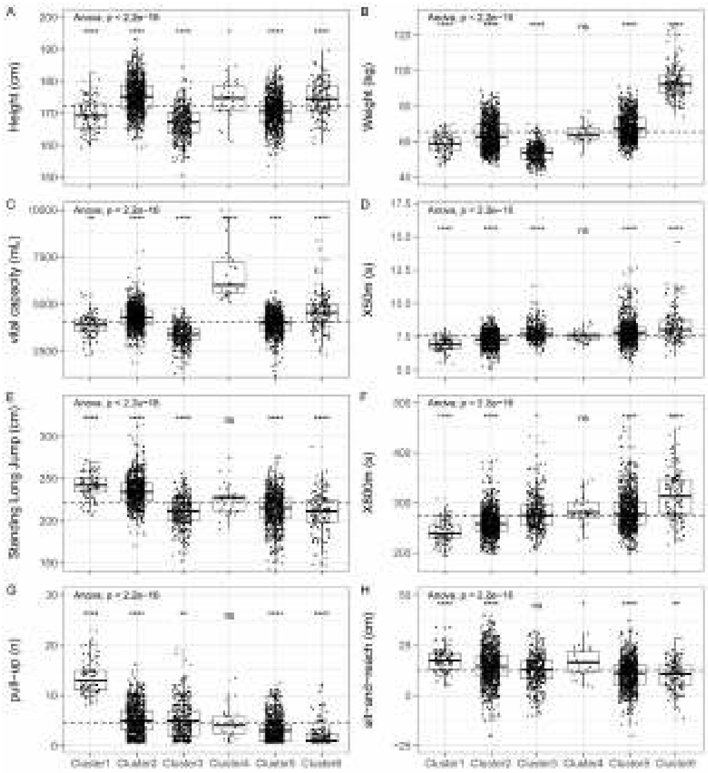

Fig.7 Diffrences within the caparisions between (A) Cluster 1 - (F) Cluster 6 to base level by ANOVA for male categories:**** $p<0.001$, *** $p<0.001$, ** $p<0.01$, * $p<0.05$ and ns represents no significant.

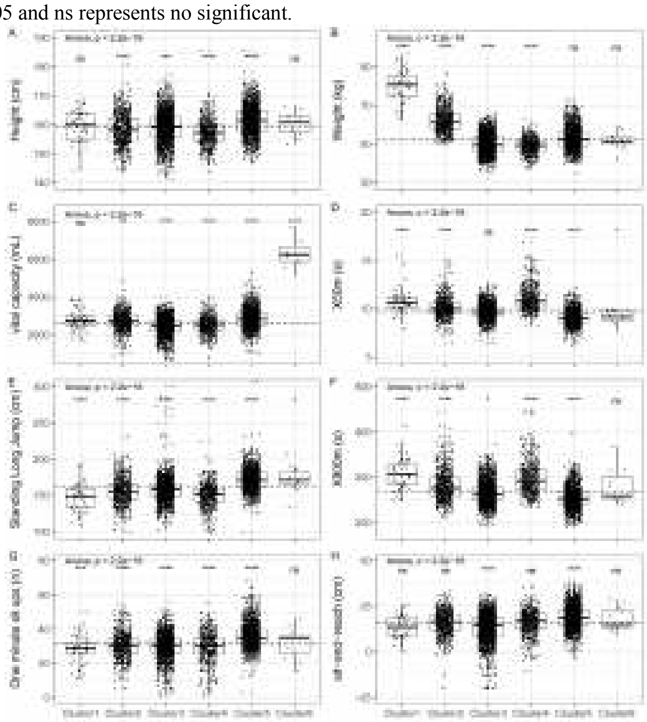

Fig.8 Diffrences within the caparisions between (A) Cluster 1 - (F) Cluster 6 to base level by ANOVA for female categories:**** $p<0.001$, *** $p<0.001$, ** $p<0.01$, * $p<0.05$ and ns represents no significant.

Relative Imoportance of Physique Indicators

PCA results reveal the relative importance of the total 8 variables in male categories and female categories, respectively. The PCA could identify the relative important variables for their sensitivity to phyaical fitness in each cluster category. As shown in Fig. 9, Height is a relative most important factor of influencing male physical fitness for almost all cluster categories (except Cluster 3). The Pullup is relative sensitive to physical fitness in Clusters 1, 3 and 4 (Fig. 9A,9C,9D). Other sensitive indicators to physical fitness include X50m for Cluster 2 and Cluster 3 (Figs. 9B,9C), Lung for Cluster 2 and Cluster 6 (Fig. 9B,9F), as well as Jump for Cluster 1 and Cluster 5 (Fig. 9A,9E). As shown in Fig. 10, the Height is also the relative most important factor of influencing physical fitness to female college students for all Cluster categories. Then, Weight shows relative sensitive to physical fitness except in Clusters 3 (Fig. 10C). Other sensitive indicators to physical fitness in female college students include X800m for Cluster1, Cluster 2 and Cluster 3 (Figs. 9A,9B,9C), X50m for Cluster 2, Cluster 3 and Cluster 6 (Fig. 9B,9C,9F), as well as Jump for Cluster 4, Cluster 5 and Cluster 6 (Fig. 9D,9E,9F). It should be noted that the small sample data could have an impact on the results in accuracy. The accuracy could be promoted or optimized with the increase of sample size. Anyhow, the current results show the significant differences which could support our conclustions.

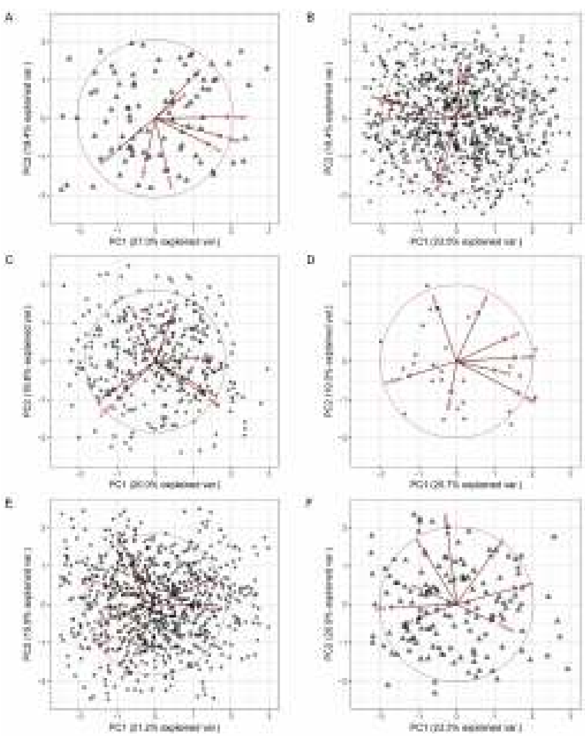

Fig.9 The relative importance indicator of physical fitness for (A) Cluster 1 to (F) Cluster 6 in male categories

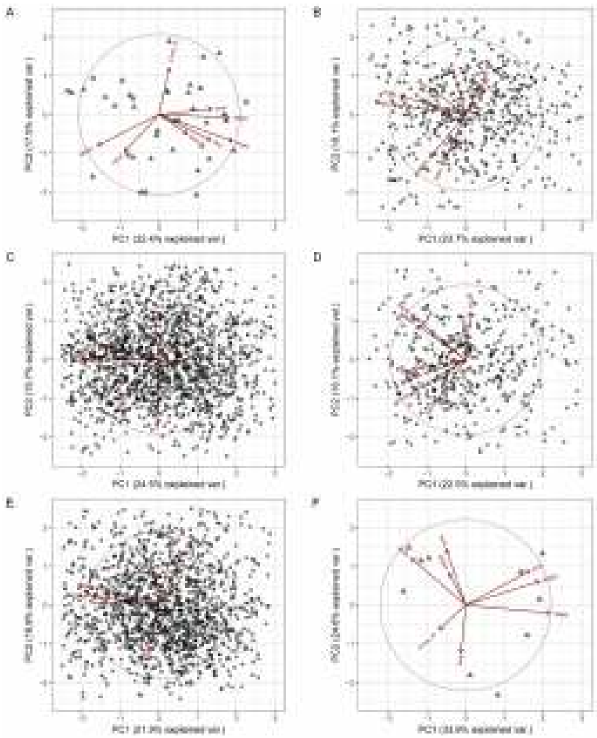

Fig.10 The relative importance indicator of physical fitness for (A) Cluster 1 to (F) Cluster 6 in female categories

Dicussion

The main contribution of this study is the supervised SOM analysis on physique indicators of college students. The analysis allow a non-lineal visual interpretation of mulitple variables with emphasis on the concerned indicator. The higher the data volume has, the more obvious the classification feature is. Concretely, this analysis enables college administrators to detect specific physical fitness profile of students and really concern about the effects of regular physical activities on changes in the profiles of the participants.

For a typical SOM, it consists of two layers: an input layer and an output layer. The number of output neurons in SOM training are sometimes arbitrary. There are no strict rules. In the present study, we trained the SOM with different map sizes and selected 400 (N = 20□20) as the appropriate number of output neurons based on a heuristic equation (Vesanto & Alhoniemi, 2000). It shold be note that the metioned equation by Vesanto and Alhoniemi was realy a very rough estimate to determine the neuron number of output network. In additon, during the typical learning process for a SOM, each input vector is assigned to one output neuron through SOM calculation. The coeffecents of the input and output establish a link between the input units and their associated output units. The learning progresses of iterative loops relay on the comparision with the best matching unit until a stopping criterion is met. In the present study, we chose 100 iterations to achieve the relative small value of mean distance to closest uint. The larger interations, the more time-consuming and more complexity of the algorithm (Wongravee, Lloyd, Silwood, Grootveld, & Brereton, 2010). In addition, it should be emphasized that the data structure and distribution of BMI in the case, have great influences on the SOM mapping due to the gathered similar values in BMI indicator. Moreover, it was revealed by the results of less samples in Cluster 4 in male and Cluster 1 and Cluster 6 in female. However, this defect can be overcomed or optimized with much more data inputs.

On the record data of the study, 6 clusters are classified using WCSS method in SOM for both male and female students. In cluster analysis, WCSS is the most used criteria in minimizing the Euclidean distances from each object to the centroid of the cluster to which it belongs (Duong & Vrain, 2015). Finding a global optimum for this criterion is a NP-Hard (Non-deterministic Polynomial) problem and even finding a good lower bound is difficult (Aloise, Deshpande, Hansen, & Popat, 2009). The optimal cluster number can't be calculated directly.

This uncertainty can be revealed partly by the method of exhaustion as the proper optimal cluster number. Other criterions of optimum cluster number also exist the similar uncertainty, such as partitioning around medoids (Van der Laan, Pollard, & Bryan, 2003), Caliński criterion (Richards, Holmans, O'Donovan, Owen, & Jones, 2008), affinity propagation method (Bodenhofer, Kothmeier, & Hochreiter, 2011), average silhouette method (Hanisch, Zien, Zimmer, & Lengauer, 2002), clustergram by Matthias Schonlau (Schonlau, 2002) and so on. In our results, the defect of unbalance with sample size distribution in cluster categories provided the evidence for better selection of cluster number after the invalidation of increasing the sample amount.

In the validation for the differences in classified clusters, we chose the base level (average level of all data in each indicator) as the benchmark for comparisions in ANOVA. In the study, we only concerned the differences of classified categories rather than the pairwise comparison. The results of ANOVA confirmed the differences of cluster categories with the comparions to the base level. In the process of the relative importance by PCA, we noticed the unbalance with sample size distribution in cluster categories again, and the accuracy of the PCA results in Clusters with small sample (such as Cluster 4 in male, Cluster 1 and Cluter 6 in female) should be applied carefully when the conclusion was drawn based on the results. In addition, the supervised SOM was only employed for classification rather than predition. In future, more datasets and the application of supervised SOM predition should be considered.

Conclusions

We analyzed the classifications of physical fitness data of college students in northern China, as well as the validation and evaluation for the classificaitons. The data classification were conducted by supervised SOM based on BMI. The diffrences of classified data were validated using ANOVA method, and PCA displayed the evaluation of the relative importance of all indicators for each classification. Our conclusions are as follows:(1) The supervised SOM provided the intuitive and visual characteristics of classification for physical fitness data with emphasis on the BMI;(2) The classifications coupled with BMI were validated by ANOVA and the relative importance indicators were analyzed by PCA in each classification. Physique indicator showed heterogeneity in different classifications. Height and Pulup were prone to the relative importance for male students, but Weight for female students.(3) the methods presented here were universally applicable, and the better performance could be promoted with much more data input.

This study can be extended to other region in the world for evaluating or evaluated physical fitness, and the object is not limited to college students. The data analysis in this study could be easily replicated for the conveniency and availability of other data. The evaluation of physical fitness with emphasis on overweight or obesity population could also be conducted in other regions. Therefore, the implications of this work could be more global. Anyhow, the results and the relevant methods presented here are valuable for deepening our understanding BMI effects on physical fitness and can be used to develop a practical strategy for effective physical activities.

Conflicts of interest - The authors have declared no conflict of interest

References:

Aloise, D., Deshpande, A., Hansen, P., & Popat, P. (2009). NP-hardness of Euclidean sum-of-squares clustering. *Machine learning, 75*(2), 245-248.

Bodenhofer, U., Kothmeier, A., & Hochreiter, S. (2011). APCluster: an R package for affinity propagation clustering. *Bioinformatics, 27*(17), 2463-2464.

Calle, E. E., Rodriguez, C., Walker-Thurmond, K., & Thun, M. J. (2003). Overweight, obesity, and mortality from cancer in a prospectively studied cohort of US adults. *N Engl j Med, 2003*(348), 1625-1638.

Collaboration, B. P. L. T. T. (2015). Effects of blood pressure lowering on cardiovascular risk according to baseline body-mass index: a meta-analysis of randomised trials. *The Lancet, 385*(9971), 867-874.

Collaboration, G. B. M. (2016). Body-mass index and all-cause mortality: individual-participant-data meta-analysis of 239 prospective studies in four continents. *The Lancet, 388*(10046), 776-786.

Collaboration, P. S. (2009). Body-mass index and cause-specific mortality in 900 000 adults: collaborative analyses of 57 prospective studies. *The Lancet, 373*(9669), 1083-1096.

Crews, R. T., Schneider, K. L., Yalla, S. V., Reeves, N. D., & Vileikyte, L. (2016). Physiological and psychological challenges of increasing physical activity and exercise in patients at risk of diabetic foot ulcers: a critical review. *Diabetes/metabolism research and reviews, 32*(8), 791-804.

Cuss, C., & Guéguen, C. (2016). Analysis of dissolved organic matter fluorescence using self-organizing maps: mini-review and tutorial. *Analytical Methods, 8*(4), 716-725.

Dolton, P., & Xiao, M. (2015). The intergenerational transmission of BMI in China. *Economics & Human Biology, 19*, 90-113.

Duong, K.-C., & Vrain, C. (2015). *Constrained minimum sum of squares clustering by constraint programming.* Paper presented at the International Conference on Principles and Practice of Constraint Programming.

Finucane, M. M., Stevens, G. A., Cowan, M. J., Danaei, G., Lin, J. K., Paciorek, C. J., . . . Bahalim, A. N. (2011). National, regional, and global trends in body-mass index since 1980: systematic analysis of health examination surveys and epidemiological studies with 960 country-years and 9· 1 million

participants. *The Lancet, 377*(9765), 557-567.
Flegal, K. M., Kit, B. K., Orpana, H., & Graubard, B. I. (2013). Association of all-cause mortality with overweight and obesity using standard body mass index categories: a systematic review and meta-analysis. *Jama, 309*(1), 71-82.
Gu, D., Reynolds, K., Wu, X., Chen, J., Duan, X., Reynolds, R. F., . . . Group, I. C. (2005). Prevalence of the metabolic syndrome and overweight among adults in China. *The Lancet, 365*(9468), 1398-1405.
Hanisch, D., Zien, A., Zimmer, R., & Lengauer, T. (2002). Co-clustering of biological networks and gene expression data. *Bioinformatics, 18*(suppl_1), S145-S154.
He, W., Li, Q., Yang, M., Jiao, J., Ma, X., Zhou, Y., . . . Zhu, S. (2015). Lower BMI cutoffs to define overweight and obesity in China. *Obesity, 23*(3), 684-691.
Joseph, C., LoBue, V., Rivera, L. M., Irving, J., Savoy, S., & Shiffrar, M. (2016). An attentional bias for thin bodies and its relation to body dissatisfaction. *Body image, 19*, 216-223.
Kabisch, N., van den Bosch, M., & Lafortezza, R. (2017). The health benefits of nature-based solutions to urbanization challenges for children and the elderly – A systematic review. *Environmental Research, 159*(Supplement C), 362-373.
Kohonen, T. (1998). The self-organizing map. *Neurocomputing, 21*(1), 1-6.
Kohonen, T. (2012). *Self-organization and associative memory* (Vol. 8): Springer Science & Business Media.
Krause, S., Ware, R., McPherson, L., Lennox, N., & O'Callaghan, M. (2016). Obesity in adolescents with intellectual disability: Prevalence and associated characteristics. *Obesity research & clinical practice, 10*(5), 520-530.
Moussally, J. M., Brosch, T., & Van der Linden, M. (2016). Time course of attentional biases toward body shapes: The impact of body dissatisfaction. *Body image, 19*, 159-168.
Park, Y.-S., Chon, T.-S., Bae, M.-J., Kim, D.-H., & Lek, S. (2018). Multivariate Data Analysis by Means of Self-Organizing Maps *Ecological Informatics* (pp. 251-272): Springer.
Pellicer-Chenoll, M., Garcia-Massó, X., Morales, J., Serra-Añó, P., Solana-Tramunt, M., González, L.-M., & Toca-Herrera, J.-L. (2015). Physical activity, physical fitness and academic achievement in adolescents: a self-organizing maps approach. *Health education research, 30*(3), 436-448.
Rao, W., Su, Y., Yang, G., Ma, Y., Liu, R., Zhang, S., . . . Yu, Y. (2016). Cross-sectional associations between body mass index and hyperlipidemia among adults in northeastern china. *International journal of environmental research and public health, 13*(5), 516.
Richards, A. L., Holmans, P., O'Donovan, M. C., Owen, M. J., & Jones, L. (2008). A comparison of four clustering methods for brain expression microarray data. *BMC bioinformatics, 9*(1), 490.
Roswall, N., Li, Y., Sandin, S., Ström, P., Adami, H. O., & Weiderpass, E. (2017). Changes in body mass index and waist circumference and concurrent mortality among Swedish women. *Obesity, 25*(1), 215-222.
Schonlau, M. (2002). The clustergram: A graph for visualizing hierarchical and non-hierarchical cluster analyses. *The Stata Journal, 3*, 316-327.
Singh, P. K., Pandey, A. K., & Rani, S. (2017). HYPERTENSION AND ITS RISK FACTORS-A CROSS SECTIONAL STUDY IN RURAL AREA. *Journal of Evidence Based Medicine and Healthcare, 4*(44), 2663-2667.
Tian, Y., Jiang, C., Wang, M., Cai, R., Zhang, Y., He, Z., Liu, X. (2016). BMI, leisure-time physical activity, and physical fitness in adults in China: results from a series of national surveys, 2000–14. *The Lancet Diabetes & Endocrinology, 4*(6), 487-497.
Van der Laan, M., Pollard, K., & Bryan, J. (2003). A new partitioning around medoids algorithm. *Journal of Statistical Computation and Simulation, 73*(8), 575-584.
Vesanto, J., & Alhoniemi, E. (2000). Clustering of the self-organizing map. *IEEE Transactions on neural networks, 11*(3), 586-600.
Wang, Y., Mi, J., Shan, X., Wang, Q. J., & Ge, K. (2007). Is China facing an obesity epidemic and the consequences? The trends in obesity and chronic disease in China. *International journal of obesity, 31*(1), 177-188.