A New Way of Visualizing Curricula Using Competencies: Cosine Similarity and t-SNE

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***Abstract*— This paper outlines a new way of visualizing curricula using competencies via a combination of cosine similarity, t-distributed stochastic neighbor embedding (t - SNE) methods, and scatter plotting. We have already published a report on the use of multidimensional scaling with the same methods. In this report we show that a t-distributed stochastic neighbor embedding method is more useful than a multidimensional scaling method. We believe that this visualization will be useful when students select their courses.**

Keywords—new way of visualizing curricula; competency; cosine similarity; multidimensional scaling methods; scatter plotting

I. INTRODUCTION

We reported on the enhanced collaboration between faculty and staff at Kobe Tokiwa University using a Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis as well as a complex network analysis [1] at the 2016 5th International Conference on Data Science and Institutional Research (DSIR 2016). Our results led to university reform in higher education at Kobe Tokiwa University, as a part of which the university integrated its accession policy (AP), curriculum policy (CP), and diploma policy (DP). Although the university already had these three policies in place, there were no relationships between them. To integrate them, the university proposed a new policy, the “Student Support Policy” (SSP). To evaluate and connect the aforementioned policies (AP, CP, DP, assessment policy (ASP), and SSP), we needed to create a common evaluation indicator. We developed a list of the 19 Tokiwa competencies that students acquire through regular, quasi-regular, and extra-curricular courses [2]. To evaluate these policies, Kobe Tokiwa University created a common evaluation indicator called “Tokiwa competencies” (TABLE I).

TABLE I. TOKIWA COMPETENCIES FROM THE STUDENT HANDBOOK OF KOBE TOKIWA UNIVERSITY

Abbreviated Name of Competency	Competency
1. Culture	Ability to use liberal arts as the foundation of human nature, which can involve a variety of people.
2. Common Sense	Ability to behave sensibly and show sound judgment in practical matters.
3. Professionalism/Expertise	Having the necessary knowledge and skills to perform the duties of each profession
4. Media Literacy	Ability to collect, organize, and analyze necessary information from various media sources for proper thinking and judgment.
5. Logical Thinking	Ability to consider situations logically based on evidence.
6. Critical Thinking	Ability to have a multilateral, critical perspective that can grasp and consider various ideas.
7. Intellectual Curiosity	Ability to be curious, to learn and remember things, and to have fun and take pleasure in learning.
8. Exploration	Ability to think deeply about things and methods.
9. Continuity	Ability to maintain a consistent stance on issues and act knowledgeably and thoughtfully.
10. Self-Management	Ability to manage one's physical and mental health appropriately.
11. Reflection	Ability to continually seek ways to improve oneself by reflecting on one's thinking and behavior.
12. Design Thinking	Ability to design solutions and develop comprehensive knowledge.
13. Presentation	Ability to appropriately communicate one's personal feelings and thoughts to others.
14. Judgment	Ability to make appropriate decisions given the circumstances, based on valid information and sound thinking.
15. Implementation	Ability to take specific actions based on one's feelings and thoughts and without fear of failure.
16. Responsibility	Ability to behave and face things responsibly as a member of society.
17. Contribution	Ability to feel happy for others and take actions that are useful for others.
18. Communication	Ability to listen to others' opinions, without which it is impossible to have a creative dialogue.
19. Cooperation & Collaboration	Ability to set aside personal and individual interests to work together harmoniously.

MEXT has established the requirement that universities in Japan build curriculum maps [3]. A curriculum map, which is similar to a network or graph, is important for university students to learn and for academic faculty to teach, but because building a curriculum map is time-intensive, many universities do not construct curriculum maps every year. We tried to construct a curriculum map *in silico*; unfortunately, however, we could not obtain good results visualizing it as a network or graph because the extensive network of relationships was much too intricate when expressed with edges or lines on a curriculum map.

From 2017 Kobe Tokiwa university started offering a program of 40 common liberal and general education courses. Fortunately, we were able to use a rubric for all the syllabi to evaluate the courses, which revealed the relationships among the 19 competencies in the rubric (TABLE II).

Next we reported our investigation of a novel visualization of the curricula as "Novel visualization for curriculum *in silico* using syllabus by a combination of cosine similarity, multidimensional scaling methods, and scatter plot: Dynamic curriculum mapping (DCM) for syllabus" [4] in the bulletin of Kobe Tokiwa University in 2017.

Using DCM methods instead of a network or graph to visualize the relationships between curricula yielded good results. However, the latest figures created by computer differ from the usual curriculum mapping created by humans. To address this problem, in our next step we used competencies instead of syllabi to visualize the curricula.

We reported this research at the 6th DSIR 2017 [5]. This method is more useful using competencies than using syllabi.

Starting in 2018, in addition to the 40 common liberal and general education courses, Kobe Tokiwa University added additional syllabi of more than 200 courses in basic education, for which it was necessary to show the relationships among the 19 competencies in the rubric. In this case, the figures obtained by visualizing curricula based on competencies and using cosine similarity, MDS methods, and scatter plotting are much more complex than the map of 40 common liberal and general education courses.

We thus investigated other methods to reduce dimensions. Methods to reduce dimensions can generally be classified into two types, linear and nonlinear. Among the linear cases, methods such as Random Projection [6], PCA [7], and Linear Discriminant Analysis [8] are widely known.

Conversely, in the nonlinear case, there are such techniques as Isomap [9], Locally Linear Embedding [10], Modified Locally Linear Embedding (MLLE) [11], Hessian Eigenmapping [12], Local Tangent Space Alignment [13], multi-dimensional scaling (MDS) [14], and t-distributed stochastic neighbor embedding (t-SNE) [15].

Linear dimension reduction methods have existed for a long time, but many of the nonlinear dimensional reduction methods have only been developed since 2000.

In particular, t-SNE methods have recently been used in bioinformatics [16] with good results. Thus, we applied t-SNE methods instead of MDS methods.

TABLE II. THE 19 TOKIWA COMPETENCIES FOR THE 40 COURSES

Competency Course Name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Total
01.Pleasant & Deep Learning I	0	0	0	0	0	0	0	20	0	10	25	10	15	0	0	0	0	0	20	100
02.Pleasant & Deep Learning II	0	0	0	0	0	0	0	20	0	10	25	10	15	0	0	0	0	0	20	100
03.Freshman Seminar I	0	0	0	0	0	0	25	35	0	0	20	0	0	0	0	0	0	20	0	100
04.Freshman Seminar II	0	0	0	0	0	0	25	35	0	0	20	0	0	0	0	0	0	20	0	100
05.Leadership & Facilitation	0	0	0	0	0	0	0	0	0	0	40	15	0	0	0	10	10	5	20	100
06.Information Technology Basic	35	0	0	35	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
07.Health & Sports Science II	0	0	0	0	0	0	0	0	0	30	0	0	30	0	0	20	0	0	20	100
08.Academic writing	0	0	0	15	25	15	25	0	0	0	0	0	15	5	0	0	0	0	0	100
09.English Communication I	0	0	0	19	30	23	15	0	0	0	0	0	13	0	0	0	0	0	0	100
10.English Communication II	0	0	0	10	35	35	10	0	0	0	0	0	10	0	0	0	0	0	0	100
11.Communicative English Basic	0	0	0	0	0	0	20	0	0	0	0	0	60	0	0	0	0	20	0	100
12.Communicative English Intermediate	0	0	0	0	0	0	25	0	0	0	0	0	60	0	0	0	0	15	0	100
13.Sign Language	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	10	100
14.Life & Symbiosis	20	0	5	25	0	10	0	40	0	0	0	0	0	0	0	0	0	0	0	100
15.Global Environment	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	100
16.Mathematics	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	50	100
17.Statistics	0	0	0	25	25	0	0	0	0	0	0	0	0	0	0	0	0	0	50	100
18.Physics	35	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	30	100
19.Chemistry	28.5	0	0	0	21	0	28.5	8	0	0	0	0	8	0	3	0	3	0	0	100
20.Mystery of the Human Body	30	0	0	10	0	0	20	0	0	10	10	0	10	0	0	0	0	10	0	100
21.Life science	40	0	0	0	20	15	0	0	0	0	0	0	20	0	0	0	5	0	0	100
22.Safety Science	20	20	0	20	0	0	0	0	0	0	0	0	0	0	0	20	0	0	20	100
23.Agriculture	20	25	0	0	0	5	10	17.5	0	0	0	0	5	0	0	12.5	5	0	0	100
24.Introduction to Programming	0	0	0	0	30	0	0	0	0	0	0	45	0	0	0	0	25	0	0	100
25.Philosophy	0	0	0	0	25	50	0	0	0	0	0	0	25	0	0	0	0	0	0	100
26.Theory of Arts and Culture	35	0	0	0	0	0	40	0	0	0	25	0	0	0	0	0	0	0	0	100
27.Literature	10	0	0	0	20	0	0	0	0	0	10	0	40	0	0	10	0	10	0	100
28.Current Events in the World	35	0	0	0	0	0	25	20	0	0	0	20	0	0	0	0	0	0	0	100
29.Modern Sociology	20	0	0	20	30	30	0	0	0	0	0	0	0	0	0	0	0	0	0	100
30.Economics	0	30	0	0	30	0	20	0	0	0	0	0	20	0	0	0	0	0	0	100
31.Clinical Psychology	0	0	24	0	0	24	0	0	0	0	0	0	24	0	0	0	0	24	4	100
32.Human Relations Theory	0	0	24	0	0	24	0	0	0	0	0	0	23	0	0	0	0	24	5	100
33.Education & Human	60	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	20	0	100
34.Collaboration with the Community I	0	10	0	0	0	0	0	0	0	0	50	0	0	0	10	10	10	0	10	100
35.Disaster and Community Development	0	0	0	0	0	0	0	25	25	0	0	0	0	0	0	25	25	0	0	100
36.Community Design	0	0	0	15	15	15	0	10	0	0	0	25	20	0	0	0	0	0	0	100
37.Life Design	0	0	0	15	15	0	10	10	0	0	0	35	15	0	0	0	0	0	0	100
38.The Constitution of Japan	35	0	0	0	20	0	0	0	0	0	20	0	10	0	0	10	0	5	0	100
39.Life & Ethics	0	60	0	0	0	20	0	0	0	0	0	0	10	0	0	0	10	0	0	100
40.Japanese History	20	0	20	0	20	15	0	0	0	0	0	0	25	0	0	0	0	0	0	100

In this paper we report on the new curriculum visualization using competencies via cosine similarity, t-SNE methods, and scatter plotting, and we will compare the result of t-SNE and MDS methods.

II. METHODS

Cosine similarity can be used to measure the differences between documents. Cosine similarity is defined by:

$$\cos(\overrightarrow{a}, \overrightarrow{b}) := \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} = \frac{\sum_{i=1}^{|V|} a_i b_i}{\sqrt{\sum_{i=1}^{|V|} a_i^2} \cdot \sqrt{\sum_{i=1}^{|V|} b_i^2}}$$

Cosine similarity is a measure of the similarity between two vectors. In this paper, the vector encodes a syllabus or course's pattern of 19 competencies, and cosine similarity is used to measure the similarity between two syllabi or courses (TABLE II). The maximum value of cosine similarity is 1 and the minimum is −1. When two syllabi or patterns of competencies are the same, then the cosine similarity is 1.

It is easy to calculate the cosine similarity of competencies. To calculate the cosine similarity of syllabi, we prepared a vector space in which each vector represents the syllabus of a course offered by Kobe Tokiwa University in 2017. Each syllabus is freely available on the institution's official homepage [17].

We visualized the cosine similarity matrix using t-SNE methods with the R package "tsne" [18] and multidimensional scaling (MDS) methods were implemented using the R package "lsa" (latent semantic analysis) [19], scatter plotting, and the "maptools" package [20] using R [21].

III. RESULTS AND DISCUSSION

We developed a new way to visualize curricula using syllabi via a combination of cosine similarity, MDS, and scatter plotting [4]. We call this method dynamic curriculum mapping (DCM). Being a virtual method, DCM differs from the usual curriculum mapping created by humans. To address this problem, we used competencies instead of syllabi to visualize curricula.

We were able to prepare 40 syllabi for the common liberal and general education courses offered in 2017 (TABLE II). We used a rubric for all syllabi to evaluate their courses, and then investigated the relationships among the 19 competencies in the rubric (please see TABLE II).

In this approach, a course can be regarded as a vector with 19 dimensions. Using cosine similarity, we can calculate the whole cosine similarity between two courses. The result is ${}_{40}C_2$=780 separate values. To reduce dimensions, we changed from cosine similarity to distance.

The conventional way of visualizing a cosine similarity matrix is to map it onto distance space, thereby reducing this high dimensionality to low dimensionality (two dimensions). Unfortunately, the cosine similarity of the two vectors in the vector space is unlikely to accord with the distance axioms in a general mathematical sense (e.g., satisfying conditions of non-negativity, non-degradability, and symmetry and the triangular inequality), because cosine similarity can be negative. When any x, y, z belonging to the set X satisfy the four arbitrary guidelines below on the two-real-variable function d: X × X → **R** defined on the set X, d represents their distance and (X, d) represents their distance space in a general mathematical sense.

(1)	non-negativity:	$d(x, y) \geq 0$
(2)	non-degradability:	$x = y \Rightarrow d(x, y) = 0$
(3)	symmetry:	$d(x, y) = d(y, x)$,
(4)	triangular inequality:	$d(x, y) + d(y, z) \geq d(x, z)$

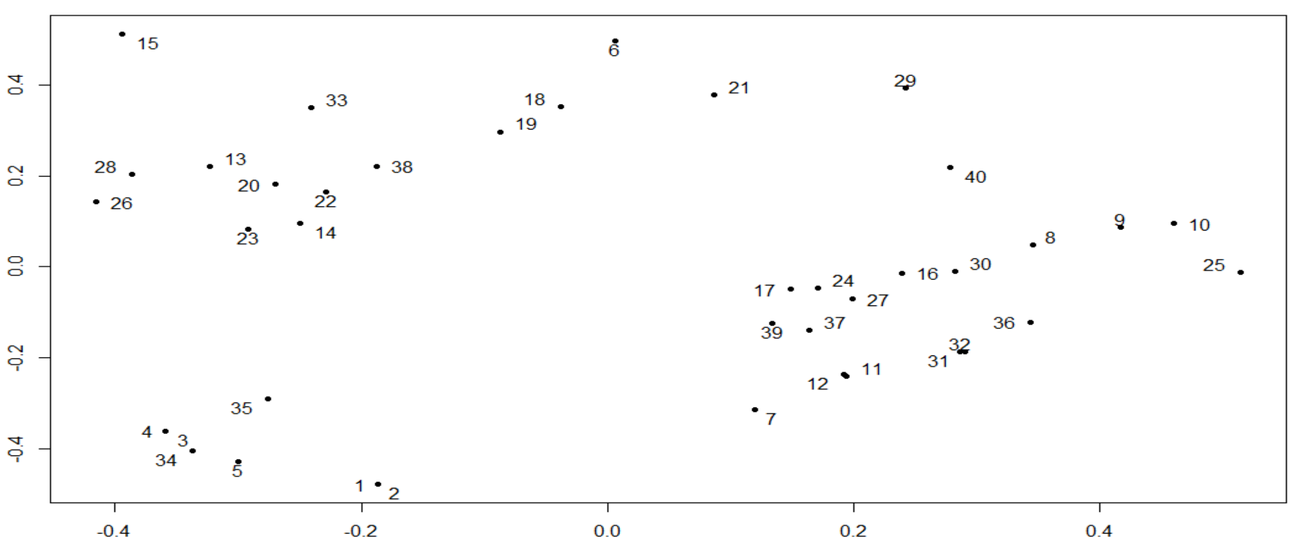

Fig. 1. Visualizing curricula using syllabi: 19 competencies for 40 courses using the MDS method.

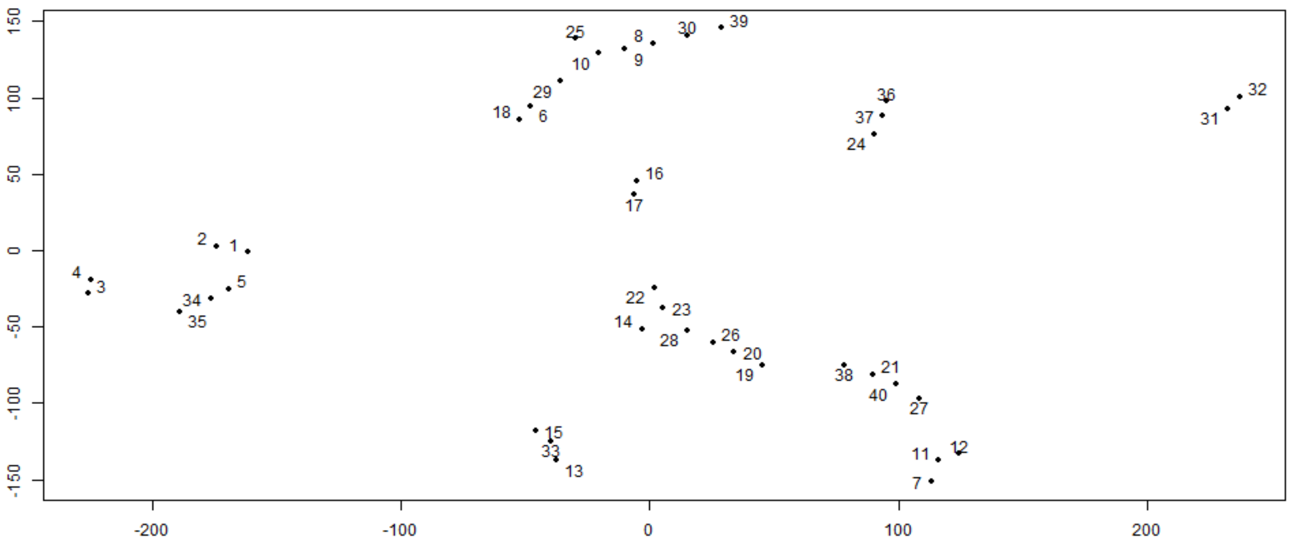

Fig. 2. Visualizing curricula using syllabi: 19 competencies for 40 courses using the t-SNE method.

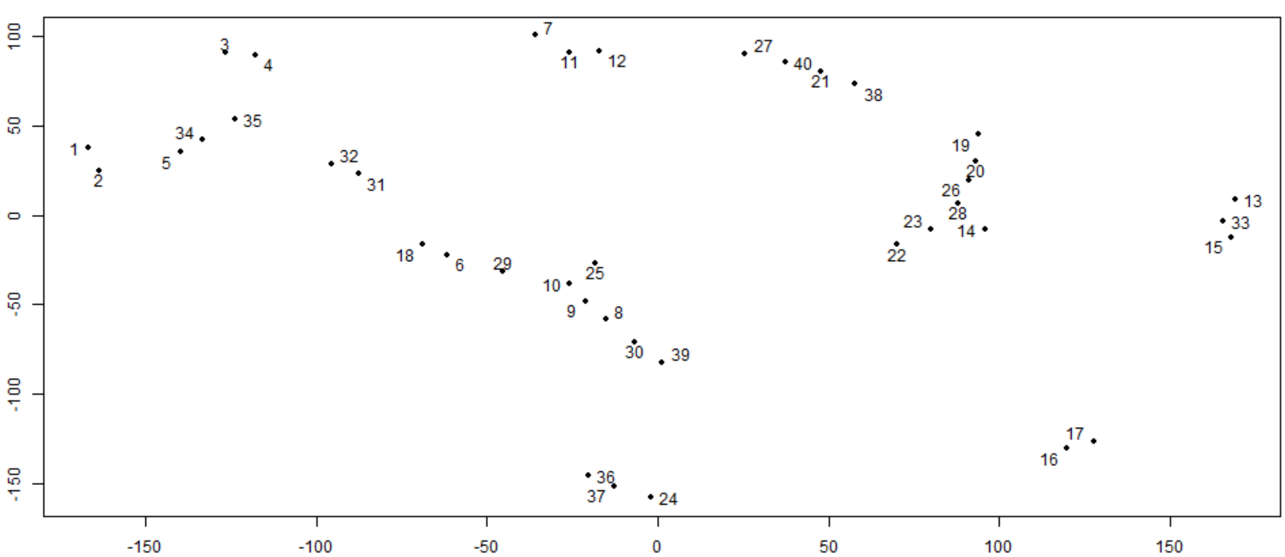

Fig. 3. Visualizing curricula using syllabi: 19 competencies for 40 courses using the t-SNE method.

Therefore, when using the visualization method described above, it is necessary for practical purposes to subtract the cosine similarity from 1 so that non-negativity is guaranteed and the values can be mapped onto the distance space. After this mapping, the maximum and minimum values of the cosine similarity are 2 and 0, respectively. This mapping also satisfies the principles of non-degradability and symmetry and the triangular inequality.

To apply DCM, we changed from cosine similarity to a distance defined as 1 – (cosine similarity), similar to the distance for MDS. Using these data (data not shown), we plotted the information in two dimensions (Fig. 1), which should be compared to the two-dimensional plot of the results of t-SNE analysis (Fig. 2). It is clear that we understand the data more easily and can more readily distinguish groups of similar courses with the t-SNE method (Fig. 2) than with MDS methods (Fig. 1).

When trying to visualize the (x, y) components obtained by dimensional reduction, in many cases they can be easily visualized on a scatter plot as developed by John Herschel in the 18th century. In this case, it is difficult to understand the meanings of the x and y axes, which correspond to the first axis and the second axis of the principal component analysis. To be precise, the values along the x and y axes are calculated after dimensional reduction. Therefore, when people who do not understand the details of dimension reduction view such a figure, it is very difficult for them to accurately understand the meaning from the figure.

Furthermore, when the dimensions are reduced, the distance in the high-dimensional space is naturally reduced as well, so we must also take into account the loss of information volume in dimensional reduction. In addition, it should also be noted that in the case of non-linear dimensionally compressed t-SNE, it is unknown how close in two dimensions two points must be to be close in the original space. Please compare Figs. 2 and 3, which were generated by the same t-SNE method. Common sense holds that if the distance is close in two dimensions, then there must be a relationship between the two, but this is mathematically incorrect. Furthermore, the closeness between the members of a group can be understood from the figure visualized in two dimensions, but one cannot argue that the grouped groups are closer to each other in the original higher-dimensional space from the features of the figure visualized in two dimensions.

We found that the t-SNE method is better than MDS methods for the purposes of displaying the similarities in curricula. In the future we will apply this method to the data for more than 200 courses offered at Kobe Tokiwa University in 2018.

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