Supplemental Material – Revisiting Dimensionality Reduction Techniques for Visual Cluster Analysis: An Empirical Study

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1 Projection results

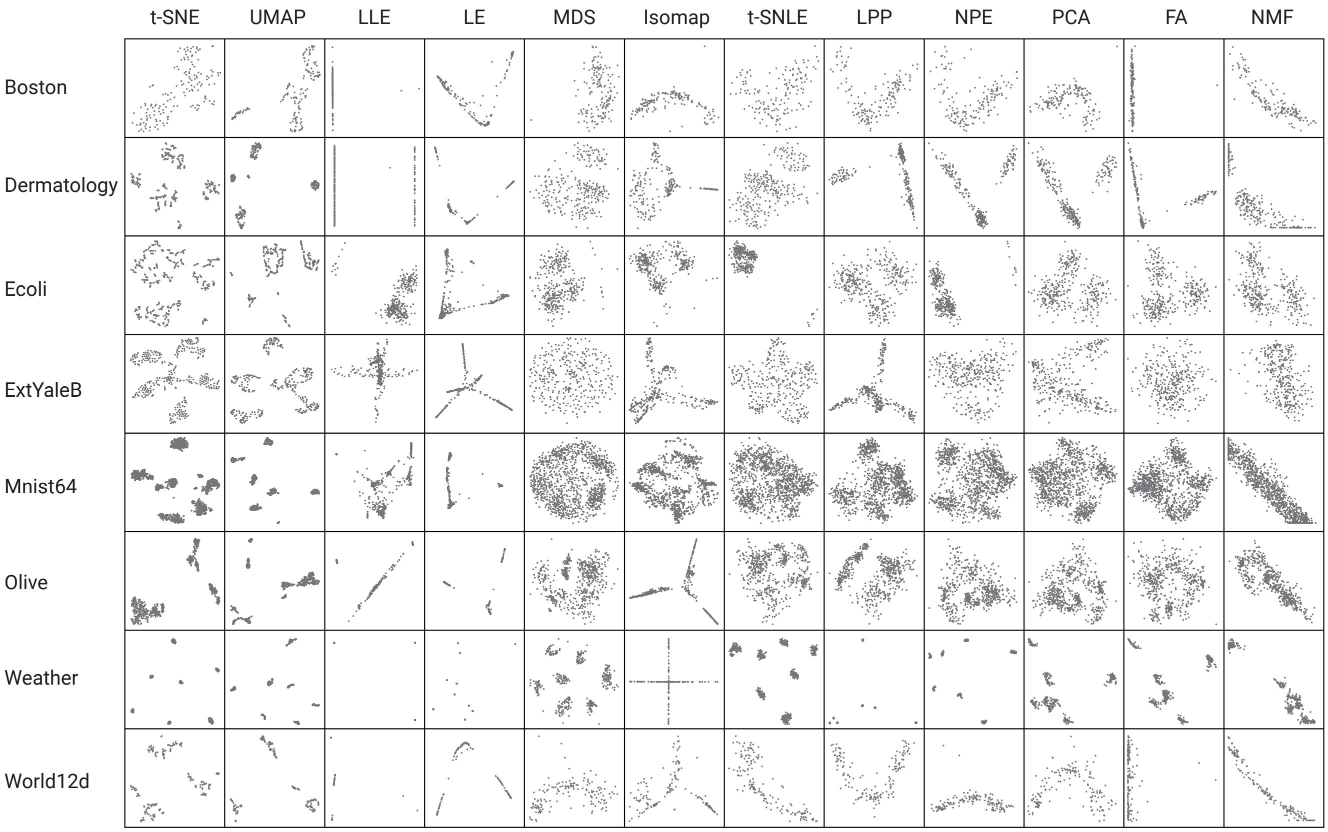

Figure 1: Projection results of twelve DR techniques on eight datasets.

2 Color-coded projection results

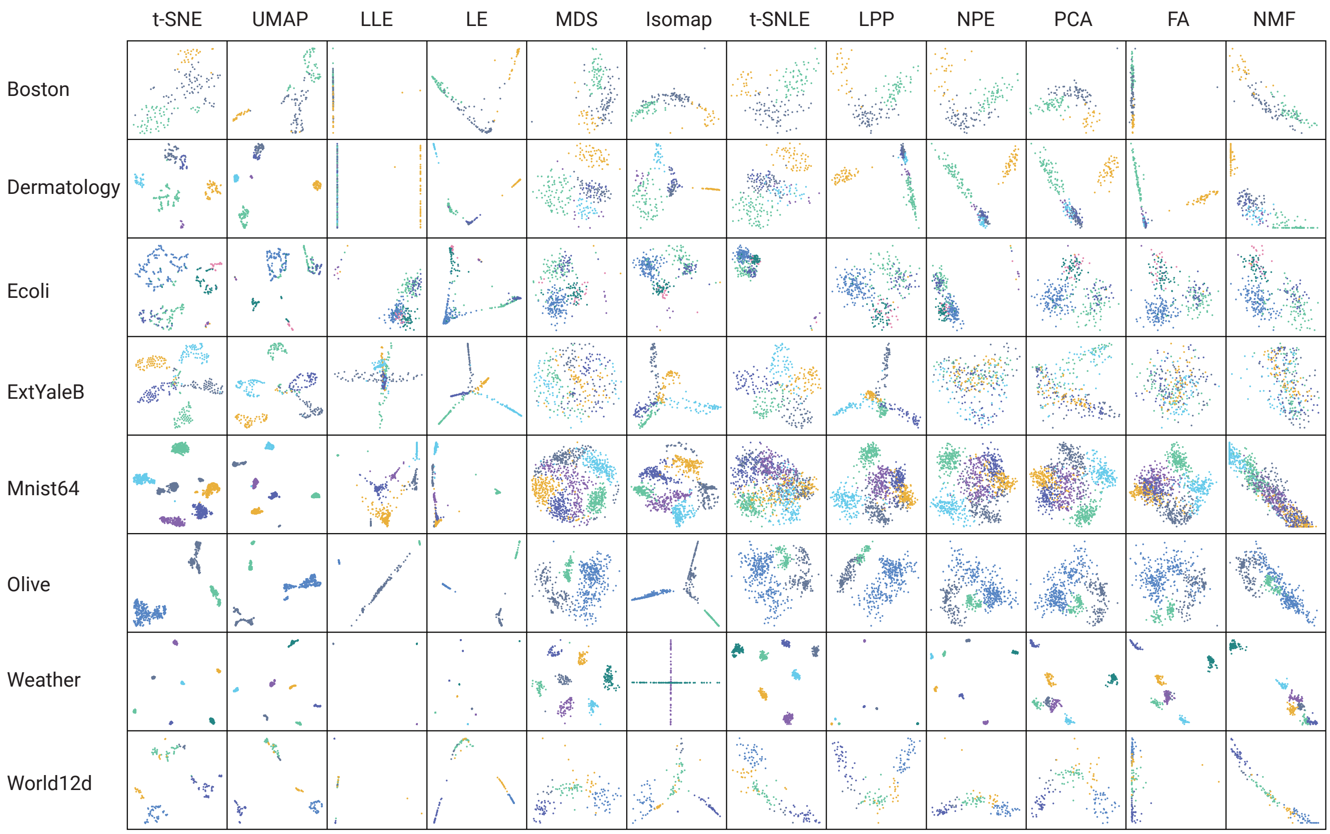

Figure 2: Color-coded projection results of twelve DR techniques on eight datasets.

3 The performance of all DR approaches on E1–E4

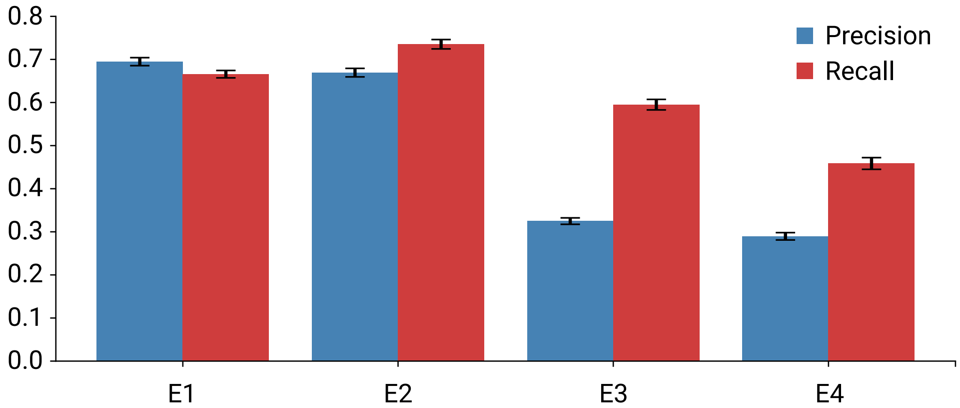

Figure 3: The performance of all DR approaches on **E1–E4**. Error bars indicate 95% confidence intervals.

4 Visual factors of cluster identification

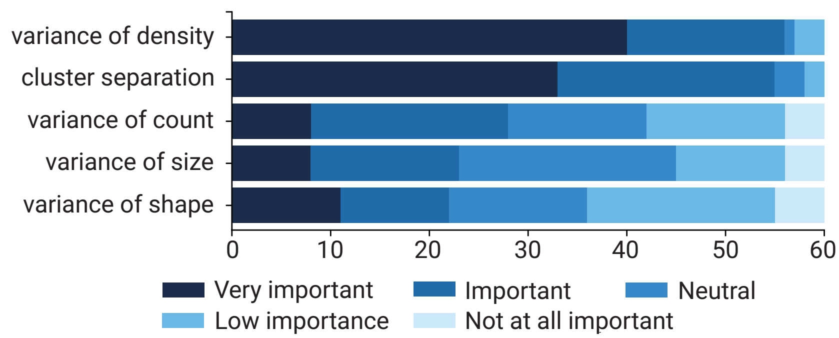

Figure 4: The importance rating of the five visual cluster separation factors.

5 Research on evaluating DR techniques in visual cluster analysis

		Etemadpour *et al.* [13]	Ventocilla *et al.* [58]	Xu *et al.* [62]	**Ours**
Tasks	Cluster identification	●	●	●	●
	Subcluster identification	●			
	Distance comparison	○			●
	Density comparison	○			●
	Membership identification	○			●
DR techqiques	FA (Factor Analysis) [37]				●
	Isomap [55]	●			●
	LE (Laplacian Eigenmaps) [3]				●
	LLE (Locally Linear Embedding) [51]				●
	LPP (Locality Preserving Projection) [22]				●
	LSP (Least Square Projection) [45]	●			
	MCML (Maximally Collapsing Metric Learning) [16]			●	
	MDS (Metric Multidimensional Scaling) [30, 25]	●			●
	NJ tree (Neighbor-Joining tree) [43]	●			
	NMF (Nonnegative Matrix Factorization) [33]				●
	NPE (Neighborhood Preserving Embedding) [21]				●
	PCA (Principal Component Analysis) [61]	●	●	●	●
	RadViz (Radial Visualizations) [23]		●		
	SC (Star Coordinates) [27]		●		
	t-SNE (t-Dist. Stochastic Neighborhood Embedding) [57]		●		●
	t-SNLE (t-Dist. Stochastic Neighborhood Linear Embedding) [6]				●
	UMAP (Uniform Manifold Approximation and Projection) [38]				●

Table 1: Summary of the differences between ours and related work, with the respective number of DR techniques(evaluated), Visual cluster analysis tasks (used in evaluation). For tasks that use colors to distinguish clusters, we use empty circles to represent them.

6 Selected papers in the literature review

Num	Name	PCA	MDS	t-SNE	UMAP	Isomap	LE	LLE	LAMP	NMF	LSP	FA	SAM
1	Rauber_EuroVis_2016 [49]			√									
2	Amorim_PacificVis_2016 [1]								√				
3	Guo_PacificVis_2014 [18]		√										
4	Zhou_PacificVis_2016 [71]		√										
5	Shen_PacificVis_2020 [52]			√									
6	Yue_TVCG_2019 [66]			√									
7	Natsukawa_TVCG_2020 [39]	√	√	√		√		√					
8	Choo_TVCG_2013 [12]			√						√			
9	Fujiwara_TVCG_2020 [15]	√			√								
10	Han_TVCG_2018 [19]			√									
11	Kahng_TVCG_2017 [26]			√									
12	Rauber_TVCG_2016 [48]			√									
13	Bernard_TVCG_2017 [4]	√	√	√									√
14	Pezzotti_TVCG_2016 [46]			√									
15	Cavallo_TVCG_2018 [9]	√	√	√		√		√					
16	Stahnke_TVCG_2015 [54]		√										
17	Kwon_TVCG_2018 [32]	√	√	√									
18	Somarakis_TVCG_2019 [53]			√									
19	Yuan_TVCG_2013 [65]	√	√										
20	Cao_TVCG_2011 [7]		√										
21	Elzen_TVCG_2015 [56]	√	√	√									
22	Oesterling_TVCG_2012 [41]	√											
23	Krueger_TVCG_2019 [29]	√			√								
24	Liu_TVCG_2018 [36]	√		√									
25	Wang_TVCG_2017 [59]	√											
26	Kwon_TVCG_2019 [31]			√									
27	Han_TVCG_2015 [20]			√									
28	Bach_TVCG_2015 [2]		√										
29	Zhao_TVCG_2019 [70]			√									
30	Kim_TVCG_2016 [28]			√									
31	Zhao_TVCG_2019 [69]			√									
32	Cheng_TVCG_2016 [11]		√										
33	Li_TVCG_2019 [35]			√									
34	Wang_TVCG_2017 [60]	√	√	√									
35	Gomez_TVCG_2015 [17]										√		
36	Pobitzer_TVCG_2012 [47]											√	
37	Favelier_TVCG_2018 [14]						√						
38	Bhattacharya_TVCG_2017 [5]						√						
39	Rossl_TVCG_2011 [50]		√										
40	Orban_TVCG_2018 [42]	√	√										
41	Yang_TVCG_2020 [64]			√									
42	Park_TVCG_2019 [44]			√									
43	Chaudhuri_TVCG_2014 [10]	√	√										
44	Zhao_TVCG_2020 [68]		√										
45	Castermans_TVCG_2018 [8]		√	√									
46	Nocaj_TVCG_2012 [40]		√										
47	Zeng_TVCG_2019 [67]			√									
48	Xu_TVCG_2019 [63]			√									
49	Höllt_TVCG_2017 [24]			√									
50	Lekschas_TVCG_2017 [34]			√									
51	Zhou_TVCG_2018 [72]			√									
Total		14	19	30	2	2	2	2	1	1	1	1	1

Table 2: DR techniques used for visual cluster analysis.

7 Interfaces for experiments

7.1 Pre-study

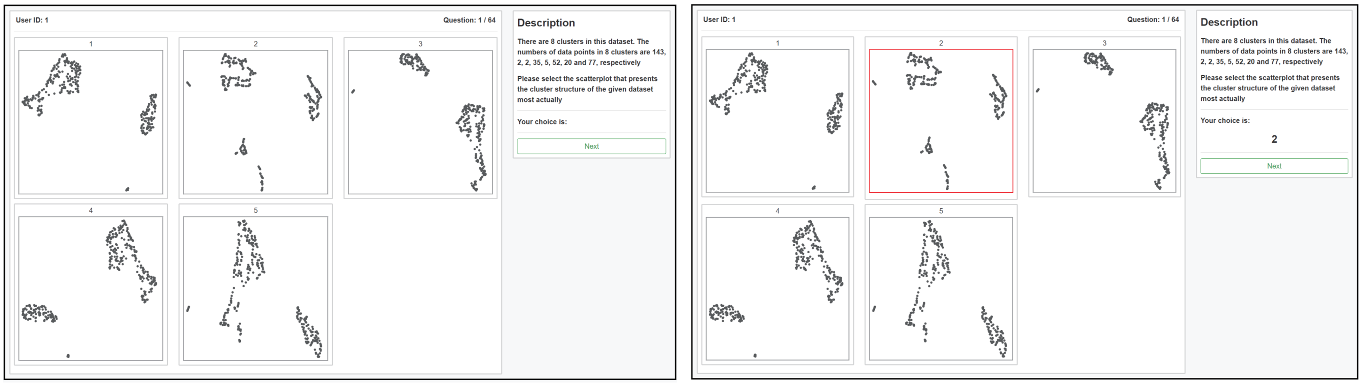

Figure 5: Example interface of **pre-study**.

7.2 Formal study

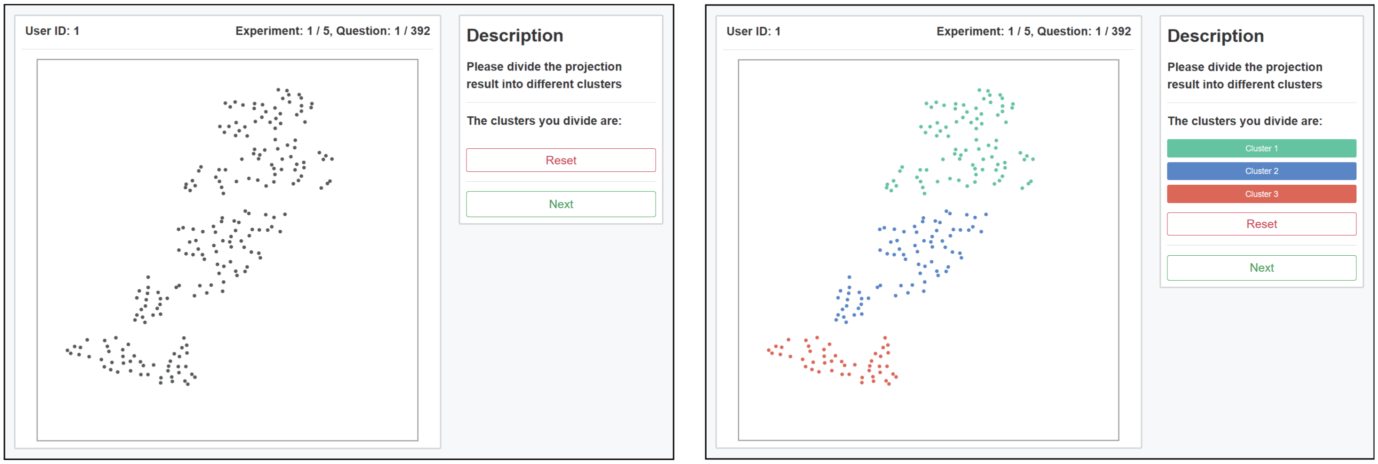

Figure 6: Example interface of **E1**(Cluster identification).

Figure 7: Example interface of **E2**(Membership identification).

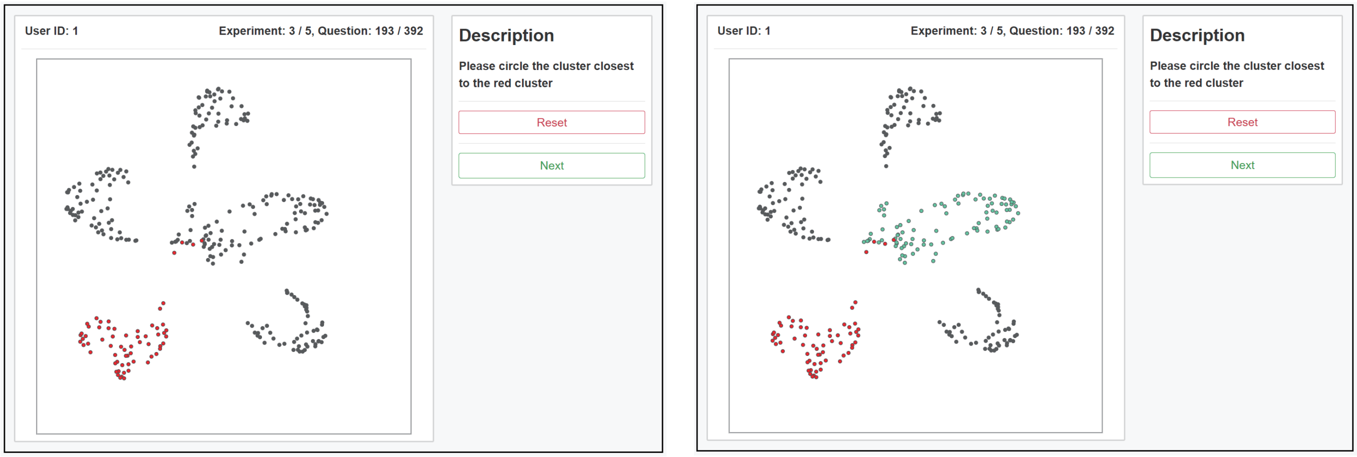

Figure 8: Example interface of **E3**(Distance comparison).

Figure 9: Example interface of **E4**(Density comparison).

Figure 10: Example interface of **E5**(Subjective study).

8 Questionnaire

8.1 Section 1: Basic information

1. Please select the range of your age.
   a) 11∼20
   b) 21∼30
   c) 31∼40
   d) 41∼50
   e) 51∼60
   f) 60+
2. Please select your gender.
   a) Male
   b) Female
3. Please specify your major or your research field.

8.2 Section 2: Visualization background

1. Are you familiar with visualization?
   a) Very unfamiliar
   b) Unfamiliar
   c) Moderately familiar
   d) Familiar
   e) Very familiar
2. Are you familiar with dimensionality reduction techniques?
   a) Very unfamiliar
   b) Unfamiliar
   c) Moderately familiar
   d) Familiar
   e) Very familiar
3. Have you ever used some dimensionality reduction techniques in visualization? If yes, please share with us the techniques, the usage scenario, and the target features to be preserved in your projection results.

8.3 Section 3: Please rate the importance of the visual factors in cluster identification

1. Variance of count?
   1) Not at all
   2) Low importance
   3) Neutral
   4) Important
   5) Very important
2. Variance of density?
   1) Not at all
   2) Low importance

3) Neutral
4) Important
5) Very important

3. Variance of size?
    1) Not at all
    2) Low importance
    3) Neutral
    4) Important
    5) Very important
4. Variance of shape?
    1) Not at all
    2) Low importance
    3) Neutral
    4) Important
    5) Very important
5. Cluster separation?
    1) Not at all
    2) Low importance
    3) Neutral
    4) Important
    5) Very important
6. Please list other visual factors that you think are also important in cluster identification.

8.4 Section 4: Please rate the importance of the four visual cluster analysis tasks

1. Cluster identification?
    1) Not at all important
    2) Low importance
    3) Neutral
    4) Important
    5) Very important
2. Membership identification?
    1) Not at all important
    2) Low importance
    3) Neutral
    4) Important
    5) Very important
3. Distance comparison?
    1) Not at all important
    2) Low importance
    3) Neutral

4) Important
5) Very important

4. Density comparison?
   1) Not at all important
   2) Low importance
   3) Neutral
   4) Important
   5) Very important
5. Cluster separation?
   1) Not at all important
   2) Low importance
   3) Neutral
   4) Important
   5) Very important
6. Please list other visual cluster analysis tasks that you think are also important?

References

[1] Elisa Amorim, Emilio Vital Brazil, Luis Gustavo Nonato, Faramarz Samavati, and Mario Costa Sousa. Multidimensional projection with radial basis function and control points selection. In *2014 IEEE Pacific Visualization Symposium*, pages 209–216. IEEE, 2014.

[2] Benjamin Bach, Conglei Shi, Nicolas Heulot, Tara Madhyastha, Tom Grabowski, and Pierre Dragicevic. Time curves: Folding time to visualize patterns of temporal evolution in data. *IEEE transactions on visualization and computer graphics*, 22(1):559–568, 2015.

[3] Mikhail Belkin and Partha Niyogi. Laplacian eigenmaps and spectral techniques for embedding and clustering. In *Proceedings of Conference on Neural Information Processing Systems*, pages 585–591, 2002.

[4] Jürgen Bernard, Marco Hutter, Matthias Zeppelzauer, Dieter Fellner, and Michael Sedlmair. Comparing visual-interactive labeling with active learning: An experimental study. *IEEE transactions on visualization and computer graphics*, 24(1):298–308, 2017.

[5] Arindam Bhattacharya, Johannes Weissenböck, Rephael Wenger, Artem Amirkhanov, Johann Kastner, and Christoph Heinzl. Interactive exploration and visualization using metatracts extracted from carbon fiber reinforced composites. *IEEE transactions on visualization and computer graphics*, 23(8):1988–2002, 2016.

[6] Kerstin Bunte, Michael Biehl, and Barbara Hammer. A general framework for dimensionality-reducing data visualization mapping. *Neural Computation*, 24(3):771–804, 2012.

[7] Nan Cao, David Gotz, Jimeng Sun, and Huamin Qu. Dicon: Interactive visual analysis of multidimensional clusters. *IEEE transactions on visualization and computer graphics*, 17(12):2581–2590, 2011.

[8] Thom Castermans, Kevin Verbeek, Bettina Speckmann, Michel A Westenberg, Rob Koopman, Shenghui Wang, Hein Van Den Berg, and Arianna Betti. Solarview: low distortion radial embedding with a focus. *IEEE transactions on visualization and computer graphics*, 25(10):2969–2982, 2018.

[9] Marco Cavallo and Çağatay Demiralp. Clustrophile 2: Guided visual clustering analysis. *IEEE transactions on visualization and computer graphics*, 25(1):267–276, 2018.

[10] Abon Chaudhuri, Teng-Yok Lee, Han-Wei Shen, and Rephael Wenger. Exploring flow fields using space-filling analysis of streamlines. *IEEE transactions on visualization and computer graphics*, 20(10):1392–1404, 2014.

[11] Shenghui Cheng and Klaus Mueller. The data context map: Fusing data and attributes into a unified display. *IEEE transactions on visualization and computer graphics*, 22(1):121–130, 2015.

[12] Jaegul Choo, Changhyun Lee, Chandan K Reddy, and Haesun Park. Utopian: User-driven topic modeling based on interactive nonnegative matrix factorization. *IEEE transactions on visualization and computer graphics*, 19(12):1992–2001, 2013.

[13] Ronak Etemadpour, Robson Motta, Jose Gustavo de Souza Paiva, Rosane Minghim, Maria Cristina Ferreira de Oliveira, and Lars Linsen. Perception-based evaluation of projection methods for multidimensional data visualization. *IEEE Transactions on Visualization and Computer Graphics*, 21(1):81–94, 2014.

[14] Guillaume Favelier, Noura Faraj, Brian Summa, and Julien Tierny. Persistence atlas for critical point variability in ensembles. *IEEE transactions on visualization and computer graphics*, 25(1):1152–1162, 2018.

[15] Takanori Fujiwara, Naohisa Sakamoto, Jorji Nonaka, Keiji Yamamoto, Kwan-Liu Ma, et al. A visual analytics framework for reviewing multivariate time-series data with dimensionality reduction. *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[16] Amir Globerson and Sam Roweis. Metric learning by collapsing classes. *Advances in neural information processing systems*, 18:451–458, 2005.

[17] Erick Gomez-Nieto, Wallace Casaca, Danilo Motta, Ivar Hartmann, Gabriel Taubin, and Luis Gustavo Nonato. Dealing with multiple requirements in geometric arrangements. *IEEE transactions on visualization and computer graphics*, 22(3):1223–1235, 2015.

[18] Hanqi Guo, Fan Hong, Qingya Shu, Jiang Zhang, Jian Huang, and Xiaoru Yuan. Scalable lagrangian-based attribute space projection for multivariate unsteady flow data. In *2014 IEEE Pacific Visualization Symposium*, pages 33–40. IEEE, 2014.

[19] Jun Han, Jun Tao, and Chaoli Wang. Flownet: A deep learning framework for clustering and selection of streamlines and stream surfaces. *IEEE transactions on visualization and computer graphics*, 26(4):1732–1744, 2018.

[20] Qi Han, Dennis Thom, Markus John, Steffen Koch, Florian Heimerl, and Thomas Ertl. Visual quality guidance for document exploration with focus+ context techniques. *IEEE transactions on visualization and computer graphics*, 26(8):2715–2731, 2019.

[21] Xiaofei He, Deng Cai, Shuicheng Yan, and Hong-Jiang Zhang. Neighborhood preserving embedding. In *Proceedings of International Conference on Computer Vision*, pages 1208–1213, 2005.

[22] Xiaofei He and Partha Niyogi. Locality preserving projections. In *Proceedings of Neural Information Processing Systems*, pages 153–160, 2004.

[23] Patrick Hoffman, Georges Grinstein, Kenneth Marx, Ivo Grosse, and Eugene Stanley. Dna visual and analytic data mining. In *Proceedings. Visualization'97 (Cat. No. 97CB36155)*, pages 437–441, 1997.

[24] Thomas Höllt, Nicola Pezzotti, Vincent van Unen, Frits Koning, Boudewijn PF Lelieveldt, and Anna Vilanova. Cyteguide: Visual guidance for hierarchical single-cell analysis. *IEEE Transactions on Visualization and Computer Graphics*, 24(1):739–748, 2017.

[25] Stephen Ingram, Tamara Munzner, and Marc Olano. Glimmer: Multilevel mds on the gpu. *IEEE Transactions on Visualization and Computer Graphics*, 15(2):249–261, 2008.

[26] Minsuk Kahng, Pierre Y Andrews, Aditya Kalro, and Duen Horng Chau. A cti v is: Visual exploration of industry-scale deep neural network models. *IEEE transactions on visualization and computer graphics*, 24(1):88–97, 2017.

[27] Eser Kandogan. Star coordinates: A multi-dimensional visualization technique with uniform treatment of dimensions. In *Proceedings of the IEEE information visualization symposium*, volume 650, page 22, 2000.

[28] Minjeong Kim, Kyeongpil Kang, Deokgun Park, Jaegul Choo, and Niklas Elmqvist. Topiclens: Efficient multi-level visual topic exploration of large-scale document collections. *IEEE transactions on visualization and computer graphics*, 23(1):151–160, 2016.

[29] Robert Krueger, Johanna Beyer, Won-Dong Jang, Nam Wook Kim, Artem Sokolov, Peter K Sorger, and Hanspeter Pfister. Facetto: Combining unsupervised and supervised learning for hierarchical phenotype analysis in multi-channel image data. *IEEE transactions on visualization and computer graphics*, 26(1):227–237, 2019.

[30] Joseph B Kruskal and Myron Wish. *Multidimensional scaling*, volume 11. 1978.

[31] Bum Chul Kwon, Min-Je Choi, Joanne Taery Kim, Edward Choi, Young Bin Kim, Soonwook Kwon, Jimeng Sun, and Jaegul Choo. Retainvis: Visual analytics with interpretable and interactive recurrent neural networks on electronic medical records. *IEEE transactions on visualization and computer graphics*, 25(1):299–309, 2018.

[32] Bum Chul Kwon, Ben Eysenbach, Janu Verma, Kenney Ng, Christopher De Filippi, Walter F Stewart, and Adam Perer. Clustervision: Visual supervision of unsupervised clustering. *IEEE transactions on visualization and computer graphics*, 24(1):142–151, 2017.

[33] Daniel D Lee and H Sebastian Seung. Algorithms for non-negative matrix factorization. In *Proceedings of Conference on Neural Information Processing Systems*, pages 556–562, 2001.

[34] Fritz Lekschas, Benjamin Bach, Peter Kerpedjiev, Nils Gehlenborg, and Hanspeter Pfister. Hipiler: visual exploration of large genome interaction matrices with interactive small multiples. *IEEE transactions on visualization and computer graphics*, 24(1):522–531, 2017.

[35] Zeyu Li, Changhong Zhang, Shichao Jia, and Jiawan Zhang. Galex: Exploring the evolution and intersection of disciplines. *IEEE transactions on visualization and computer graphics*, 26(1):1182–1192, 2019.

[36] Shusen Liu, Peer-Timo Bremer, Jayaraman J Thiagarajan, Vivek Srikumar, Bei Wang, Yarden Livnat, and Valerio Pascucci. Visual exploration of semantic relationships in neural word embeddings. *IEEE transactions on visualization and computer graphics*, 24(1):553–562, 2017.

[37] Patrick Mair. Factor analysis. In *Modern Psychometrics with R*, pages 17–61. Springer, 2018.

[38] Leland McInnes, John Healy, and James Melville. Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426*, 2018.

[39] Hiroaki Natsukawa, Ethan R Deyle, Gerald M Pao, Koji Koyamada, and George Sugihara. A visual analytics approach for ecosystem dynamics based on empirical dynamic modeling. *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[40] Arlind Nocaj and Ulrik Brandes. Organizing search results with a reference map. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2546–2555, 2012.

[41] Patrick Oesterling, Christian Heine, Gunther H Weber, and Gerik Scheuermann. Visualizing nd point clouds as topological landscape profiles to guide local data analysis. *IEEE transactions on visualization and computer graphics*, 19(3):514–526, 2012.

[42] Daniel Orban, Daniel F Keefe, Ayan Biswas, James Ahrens, and David Rogers. Drag and track: A direct manipulation interface for contextualizing data instances within a continuous parameter space. *IEEE transactions on visualization and computer graphics*, 25(1):256–266, 2018.

[43] Jose Gustavo Paiva, Laura Florian, Helio Pedrini, Guilherme Telles, and Rosane Minghim. Improved similarity trees and their application to visual data classification. *IEEE transactions on visualization and computer graphics*, 17(12):2459–2468, 2011.

[44] Ji Hwan Park, Saad Nadeem, Saeed Boorboor, Joseph Marino, and Arie E Kaufman. Cmed: Crowd analytics for medical imaging data. *IEEE transactions on visualization and computer graphics*, 2019.

[45] Fernando V Paulovich, Luis G Nonato, Rosane Minghim, and Haim Levkowitz. Least square projection: A fast high-precision multidimensional projection technique and its application to document mapping. *IEEE Transactions on Visualization and Computer Graphics*, 14(3):564–575, 2008.

[46] Nicola Pezzotti, Boudewijn PF Lelieveldt, Laurens Van Der Maaten, Thomas Höllt, Elmar Eisemann, and Anna Vilanova. Approximated and user steerable tsne for progressive visual analytics. *IEEE transactions on visualization and computer graphics*, 23(7):1739–1752, 2016.

[47] Armin Pobitzer, Alan Lež, Krešimir Matković, and Helwig Hauser. A statistics-based dimension reduction of the space of path line attributes for interactive visual flow analysis. In *2012 IEEE Pacific Visualization Symposium*, pages 113–120. IEEE, 2012.

[48] Paulo E Rauber, Samuel G Fadel, Alexandre X Falcao, and Alexandru C Telea. Visualizing the hidden activity of artificial neural networks. *IEEE transactions on visualization and computer graphics*, 23(1):101–110, 2016.

[49] Paulo E Rauber, Alexandre X Falcão, Alexandru C Telea, et al. Visualizing time-dependent data using dynamic t-sne. *Eurographics Conference on Visualization Eurographics Conference on Visualization*, 2016.

[50] Christian Rossl and Holger Theisel. Streamline embedding for 3d vector field exploration. *IEEE Transactions on Visualization and Computer Graphics*, 18(3):407–420, 2011.

[51] Sam T Roweis and Lawrence K Saul. Nonlinear dimensionality reduction by locally linear embedding. *science*, 290(5500):2323–2326, 2000.

[52] Qiaomu Shen, Yanhong Wu, Yuzhe Jiang, Wei Zeng, KH Alexis, Anna Vianova, and Huamin Qu. Visual interpretation of recurrent neural network on multi-dimensional time-series forecast. In *2020 IEEE Pacific Visualization Symposium (PacificVis)*, pages 61–70. IEEE, 2020.

[53] Antonios Somarakis, Vincent Van Unen, Frits Koning, Boudewijn Lelieveldt, and Thomas Höllt. Imacyte: Visual exploration of cellular micro-environments for imaging mass cytometry data. *IEEE transactions on visualization and computer graphics*, 27(1):98–110, 2019.

[54] Julian Stahnke, Marian Dörk, Boris Müller, and Andreas Thom. Probing projections: Interaction techniques for interpreting arrangements and errors of dimensionality reductions. *IEEE transactions on visualization and computer graphics*, 22(1):629–638, 2015.

[55] Joshua B Tenenbaum, Vin De Silva, and John C Langford. A global geometric framework for nonlinear dimensionality reduction. *science*, 290(5500):2319–2323, 2000.

[56] Stef van den Elzen, Danny Holten, Jorik Blaas, and Jarke J van Wijk. Reducing snapshots to points: A visual analytics approach to dynamic network exploration. *IEEE transactions on visualization and computer graphics*, 22(1):1–10, 2015.

[57] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(86):2579–2605, 2008.

[58] Elio Ventocilla and Maria Riveiro. A comparative user study of visualization techniques for cluster analysis of multidimensional data sets. *Information Visualization*, 19(4):318–338, 2020.

[59] Bing Wang and Klaus Mueller. The subspace voyager: exploring high-dimensional data along a continuum of salient 3d subspaces. *IEEE transactions on visualization and computer graphics*, 24(2):1204–1222, 2017.

[60] Yunhai Wang, Kang Feng, Xiaowei Chu, Jian Zhang, Chi-Wing Fu, Michael Sedlmair, Xiaohui Yu, and Baoquan Chen. A perception-driven approach to supervised dimensionality reduction for visualization. *IEEE transactions on visualization and computer graphics*, 24(5):1828–1840, 2017.

[61] Svante Wold, Kim Esbensen, and Paul Geladi. Principal component analysis. *Chemometrics and intelligent laboratory systems*, 2(1-3):37–52, 1987.

[62] Kai Xu, Leishi Zhang, Daniel Pérez, Phong H Nguyen, and Adam Ogilvie-Smith. Evaluating interactive visualization of multidimensional data projection with feature transformation. *Multimodal Technologies and Interaction*, 1(3):13, 2017.

[63] Ke Xu, Yun Wang, Leni Yang, Yifang Wang, Bo Qiao, Si Qin, Yong Xu, Haidong Zhang, and Huamin Qu. Clouddet: Interactive visual analysis of anomalous performances in cloud computing systems. *IEEE transactions on visualization and computer graphics*, 26(1):1107–1117, 2019.

[64] Yalong Yang, Maxime Cordeil, Johanna Beyer, Tim Dwyer, Kim Marriott, and Hanspeter Pfister. Embodied navigation in immersive abstract data visualization: Is overview+ detail or zooming better for 3d scatterplots? *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[65] Xiaoru Yuan, Donghao Ren, Zuchao Wang, and Cong Guo. Dimension projection matrix/tree: Interactive subspace visual exploration and analysis of high dimensional data. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2625–2633, 2013.

[66] Xuanwu Yue, Jiaxin Bai, Qinhan Liu, Yiyang Tang, Abishek Puri, Ke Li, and Huamin Qu. sportfolio: Stratified visual analysis of stock portfolios. *IEEE transactions on visualization and computer graphics*, 26(1):601–610, 2019.

[67] Haipeng Zeng, Xingbo Wang, Aoyu Wu, Yong Wang, Quan Li, Alex Endert, and Huamin Qu. Emoco: Visual analysis of emotion coherence in presentation videos. *IEEE transactions on visualization and computer graphics*, 26(1):927–937, 2019.

[68] Jian Zhao, Mingming Fan, and Mi Feng. Chartseer: Interactive steering exploratory visual analysis with machine intelligence. *IEEE Transactions on Visualization and Computer Graphics*, 2020.

[69] Jieqiong Zhao, Morteza Karimzadeh, Luke S Snyder, Chittayong Surakitbanharn, Zhenyu Cheryl Qian, and David S Ebert. Metricsvis: A visual analytics system for evaluating employee performance in public safety agencies. *IEEE transactions on visualization and computer graphics*, 26(1):1193–1203, 2019.

[70] Xun Zhao, Yanhong Wu, Dik Lun Lee, and Weiwei Cui. iforest: Interpreting random forests via visual analytics. *IEEE transactions on visualization and computer graphics*, 25(1):407–416, 2018.

[71] Fangfang Zhou, Juncai Li, Wei Huang, Ying Zhao, Xiaoru Yuan, Xing Liang, and Yang Shi. Dimension reconstruction for visual exploration of subspace clusters in high-dimensional data. In *2016 IEEE Pacific Visualization Symposium (PacificVis)*, pages 128–135. IEEE, 2016.

[72] Zhiguang Zhou, Linhao Meng, Cheng Tang, Ying Zhao, Zhiyong Guo, Miaoxin Hu, and Wei Chen. Visual abstraction of large scale geospatial origin-destination movement data. *IEEE transactions on visualization and computer graphics*, 25(1):43–53, 2018.