zbMATH Open
THE FIRST RESOURCE FOR MATHEMATICS

Bugbee, Bruce; **Bush, Brian W.**; **Gruchalla, Kenny**; **Potter, Kristin**; **Brunhart-lupo, Nicholas**; **Krishnan, Venkat**

Enabling immersive engagement in energy system models with deep learning. (English)

Zbl 07260640
Stat. Anal. Data Min. 12, No. 4, 325-337 (2019).

Summary: Complex ensembles of energy simulation models have become significant components of renewable energy research in recent years. Often the significant computational cost, high-dimensional structure, and other complexities hinder researchers from fully utilizing these data sources for knowledge building. Researchers at National Renewable Energy Laboratory have developed an immersive visualization workflow to dramatically improve user engagement and analysis capability through a combination of low-dimensional structure analysis, deep learning, and custom visualization methods. We present case studies for two energy simulation platforms.

MSC:

62 Statistics
68 Computer science

Keywords:

high-dimensional data; interactive visualization; neural networks; renewable energy; t-SNE; Tucker decomposition

Software:

Keras; TensorFlow; TensorLy; t-SNE

Full Text: DOI

References:

[1] M. Abadi et al.,Tensorflow: A system for large-scale machine learning, OSDI 16 (2016), 265-283.

[2] G. I. Allen,Regularized tensor factorizations and higher-order principal components analysis, arXiv:1202.2476, 2012.

[3] N. Brunhart-Lupo, B. W. Bush, K. Gruchalla, and S. Smith,Simulation exploration through immersive parallel planes, 2016 Workshop on Immersive Analytics (IA), IEEE, 2016, pp. 19-24.

[4] A. Buja, D. Cook, and D. F. Swayne,Interactive high-dimensional data visualization, J. Comput. Graph. Stat. 5(1) (1996), 78-99.

[5] A. Buja, J. A. McDonald, J. Michalak, and W. Stuetzle,Interactive data visualization using focusing and linking, Visualization, 1991. Proceedings of IEEE Conference on Visualization'91, IEEE, 1991, pp. 156-163.

[6] B. Bush, N. Brunhart-Lupo, B. Bugbee, V. Krishnan, K. Potter, and K. Gruchalla,Coupling visualization, simulation, and deep learning for ensemble steering of complex energy models, 2017 IEEE Workshop on Data Systems for Interactive Analysis (DSIA), IEEE, 2017, pp. 1-5.

[7] F. Chollet et al.,Keras(2015). https://keras.io

[8] W. Cole et al.,Interactions of rooftop PV deployment with the capacity expansion of the bulk power system, Appl. Energy 168 (2016), 473-481.

[9] K. Eurek et al.,Regional energy deployment system (ReEDS) model documentation: Version 2016, National Renewable Energy Laboratory (NREL), Golden, CO, 2016.

[10] Y. Gal and Z. Ghahramani,Dropout as a Bayesian approximation: Representing model uncertainty in deep learning, International Conference on Machine Learning, 2016, pp. 1050-1059.

[11] I. Goodfellow et al.,Deep learning, Vol 1, MIT Press, Cambridge, 2016. · Zbl 1373.68009

[12] K. He, X. Zhang, S. Ren, and J. Sun,Deep residual learning for image recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770-778.

[13] S. Hochreiter and J. Schmidhuber,Long short-term memory, Neural Comput. 9(8) (1997), 1735-1780.

[14] A. Inselberg and B. Dimsdale,Parallel coordinates for visualizing multi-dimensional geometry, inComputer graphics, Springer, Tokyo, 1987, 1987, 25-44.

[15] J. Kehrer and H. Hauser,Visualization and visual analysis of multifaceted scientific data: A survey, IEEE Trans. Vis. Comput. Graph. 19(3) (2013), 495-513.

[16] T. G. Kolda and B. W. Bader,Tensor decompositions and applications, SIAM Rev. 51(3) (2009), 455-500. · Zbl 1173.65029

[17] J. Kossaifi, Y. Panagakis, and M. Pantic,Tensorly: Tensor learning in python, arXiv:1610.09555, 2016. · Zbl 07049745

[18] V. Krishnan and W. Cole,Evaluating the value of high spatial resolution in national capacity expansion models using ReEDS, Power and Energy Society General Meeting (PESGM), 2016, IEEE, 2016, pp. 1-5.

[19] Y. LeCun, Y. Bengio, and G. Hinton,Deep learning, Nature 521(7553) (2015), 436-444.

[20] L. V. D. Maaten and G. Hinton,Visualizing data using t-SNE, J. Mach. Learn. Res. 9 (2008), 2579-2605. · Zbl 1225.68219

[21] T. Mai et al.,A prospective analysis of the costs, benefits, and impacts of us renewable portfolio standards, Lawrence Berkeley National Laboratory (LBNL), Berkeley, CA, 2017.

[22] A. R. Martin and M. O. Ward,High dimensional brushing for interactive exploration of multivariate data, Proceedings of the 6th Conference on Visualization'95, IEEE Computer Society, 1995, p. 271.

[23] K. Matkovi ́c et al.,Visual analytics for complex engineering systems: Hybrid visual steering of simulation ensembles, IEEE Trans. Vis. Comput. Graph. 20(12) (2014), 1803-1812.

[24] M. Melaina et al.,National economic value assessment of plug-in electric vehicles: Volume I, NREL (National Renewable Energy Laboratory (NREL), Golden, CO, 2016.

[25] H. Obermaier and K. I. Joy,Future challenges for ensemble visualization, IEEE Comput. Graph. Appl. 34(3) (2014), 8-11.

[26] S. Peterson et al.,Overview of the biomass scenario model, National Renewable Energy Laboratory (NREL), Golden, CO, 2015.

[27] T. Pfaffelmoser, M. Reitinger, and R. Westermann,Visualizing the positional and geometrical variability of isosurfaces in uncertain scalar fields, Comput. Graph. Forum 30(3) (2011), 951-960. https://doi.org/10.1111/j.1467-8659.2011.01944.x.

[28] K. Pöthkow and H.-C. Heg,Positional uncertainty of isocontours: Condition analysis and probabilistic measures, IEEE Trans. Vis. Comput. Graph. PP(99) (2010), 1-15.

[29] K. Potter, A. Wilson, P. -T. Bremer, D. Williams, C. Doutriaux, V. Pascucci, and C. R. Johnson,Ensemble-Vis: A framework for the statistical visualization of ensemble data, IEEE International Conference on Data Mining Workshops, 2009. ICDMW'09, IEEE, 2009, pp. 233-240.

[30] H. Ribiˇci ́c et al.,Visual analysis and steering of flooding simulations, IEEE Trans. Vis. Comput. Graph. 19(6) (2013), 1062-1075.

[31] J. Sanyal et al.,Noodles: A tool for visualization of numerical weather model ensemble uncertainty, IEEE Trans. Vis. Comput. Graph. 16(6) (2010), 1421-1430.

[32] M. Sedlmair et al.,Visual parameter space analysis: A conceptual framework, IEEE Trans. Vis. Comput. Graph. 20(12) (2014), 2161-2170.

[33] B. Sigrin et al.,Distributed generation market demand model (dGen): Documentation, National Renewable Energy Laboratory (NREL), Golden, CO, 2016.

[34] R. K. Srivastava, K. Greff, and J. Schmidhuber,Highway networks, arXiv:1505.00387, 2015.

[35] J. D. Sterman,Business dynamics: Systems thinking and modeling for a complex world. Number HD30.2.S7835 2000, 2000.

[36] M. Theus,High-dimensional data visualization, inHandbook of Data Visualization, Springer, Berlin, Heidelberg, 2008, 151-178. · Zbl 1145.68386

[37] L. Vimmerstedt, B. W. Bush, and S. O. Peterson,Dynamic modeling of learning in emerging energy industries: The example of advanced biofuels in the United States. The 33rd International Conference of the System Dynamics Society, Cambridge, Massachusetts, USA, 2015.

[38] J. Waser et al.,Nodes on ropes: A comprehensive data and control flow for steering ensemble simulations, IEEE Trans. Vis. Comput. Graph. 17(12) (2011), 1872-1881.

[39] R. Wiser et al.,Wind vision: A new era for wind power in the United States, Electr. J. 28(9) (2015), 120-132.

[40] L. Zhu and N. Laptev,Deep and confident prediction for time series at Uber, 2017 IEEE International Conference on Data Mining Workshops (ICDMW), IEEE, 2017, pp. 103-110.

This reference list is based on information provided by the publisher or from digital mathematics libraries. Its items are heuristically matched to zbMATH identifiers and may contain data conversion errors. It attempts to reflect the references listed in the original paper as accurately as possible without claiming the completeness or perfect precision of the matching.