Hydrol. Earth Syst. Sci. Discuss.,
https://doi.org/10.5194/hess-2018-168-RC1, 2018

Hydrology and Earth System Sciences Discussions

Interactive comment on "HESS Opinions: Deep learning as a promising avenue toward knowledge discovery in water sciences" *by* Chaopeng Shen et al.

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Received and published: 6 May 2018

General comments

This article discusses the potential benefit of deep learning models to let emerge knowledge about water science systems from hydrological data. The paper is well written, the opinion is clearly stated and the authors present their arguments based on their expertise and their understanding of deep learning techniques. I'm wondering to what extent this is new and original compared to the opinion paper of Marçais & Dreuzy (2017 - see reference below). For example, the figure presented in this former article expressly conveys the idea that DL methods could enhance the unraveling of hydrological properties from data which is the core of this current article.

Marçais, J., & de Dreuzy, J. R. (2017). Prospective interest of deep learning for hydrological inference. Groundwater, 55(5), 688-692.

I also feel that DL techniques and especially why it does work so well is still not understood by computer scientists and mathematicians. However, this article can give the impression that the "DL reasons of success" are now understood (see specific comments) paving the way for knowledge discovery in water sciences through its use. I would consider being more cautious about that as the understanding of the specific properties of DL models compared to more traditional statistical learning models is still an active area of research. This does not mean that DL has not to be widely tested for hydrologic purposes.

Specific comments

Page 1 L.20 Could you specify articles where DL shows capacities for scientific discovery?

Page 2 L.9-16. The paragraph gives the impression that DL is a "plug and play" model whereas to my knowledge building a DL model still requires intensive computer scientists' knowledges and requires use of GPUs.

Page 2 L.24. I don't think that generalization capacities of DL come from its interpolation capability. Indeed, classical neural networks have been proven (see citation below) to be universal interpolators but they do not generalize well.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. Neural networks, 2(5), 359-366.

Page 3 L.25. I agree that increase in environmental data opens new opportunities for data-driven techniques in general and particularly for DL techniques. Along with the development of spatialized, remote sensing data, I would also insist on the development of environmental observatories that collect a lot of time series, monitoring data even though they are site specific. These two types of data are complementary to advance through knowledge discovery in hydrology.

Page 6. L.6-17. This paragraph is intended to bridge the link between interrogative techniques brought in DL by the "AI neuroscience" subdiscipline and the potential of DL for knowledge discovery in water sciences. If the arguments tend to prove that such interrogative techniques enlighten the way the architecture of DL works, it does not explain the success of DL in itself. For example, the sentence L.13: "activations of recurrent neural networks can be visualized to show the control domain of certain cells, which explains its functioning" is not correct. This only explains the functioning of the architecture of the DL, not the reason of success of such a method.

There is some literature exploring the need for explanation of DL techniques. For Convolutional Neural Networks (CNNs), their understanding can be linked with wavelet theory (see reference below). Especially their capacity to extract invariants through a lot of different scale in high dimensional datasets but this is still a subject of active research. This capacity could explain their generalization capabilities especially for image datasets.

Mallat, S. (2016). Understanding deep convolutional networks. Phil. Trans. R. Soc. A, 374(2065), 20150203.

Page 7 L.8-18. It could be interesting to explore how DL techniques can improve hypothesis testing through an exploration of competing process-based models? The Structure for Unifying Multiple Modeling Alternatives (SUMMA) (see reference below) could be a start to generate process-based models with alternative hypotheses. For example, process-based models could be used to feed DL models with numerical generated data.

Clark, M. P., Nijssen, B., Lundquist, J. D., Kavetski, D., Rupp, D. E., Woods, R. A., ... & Arnold, J. R. (2015). A unified approach for processâĂŘbased hydrologic modeling: 1. Modeling concept. Water Resources Research, 51(4), 2498-2514.

Page 10 L.20-Page 11 L.24. I would add to this list the fact that water sciences provide to DL a unique challenge because hydrologic data are intrinsically heterogeneous. Building a model able to integrate these heterogeneous data might be the key toward knowledge discovery in water sciences and toward big progresses in AI.

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