Does Machine Learning Based Multi-Model Ensemble Methods Add Value over Existing Methods?

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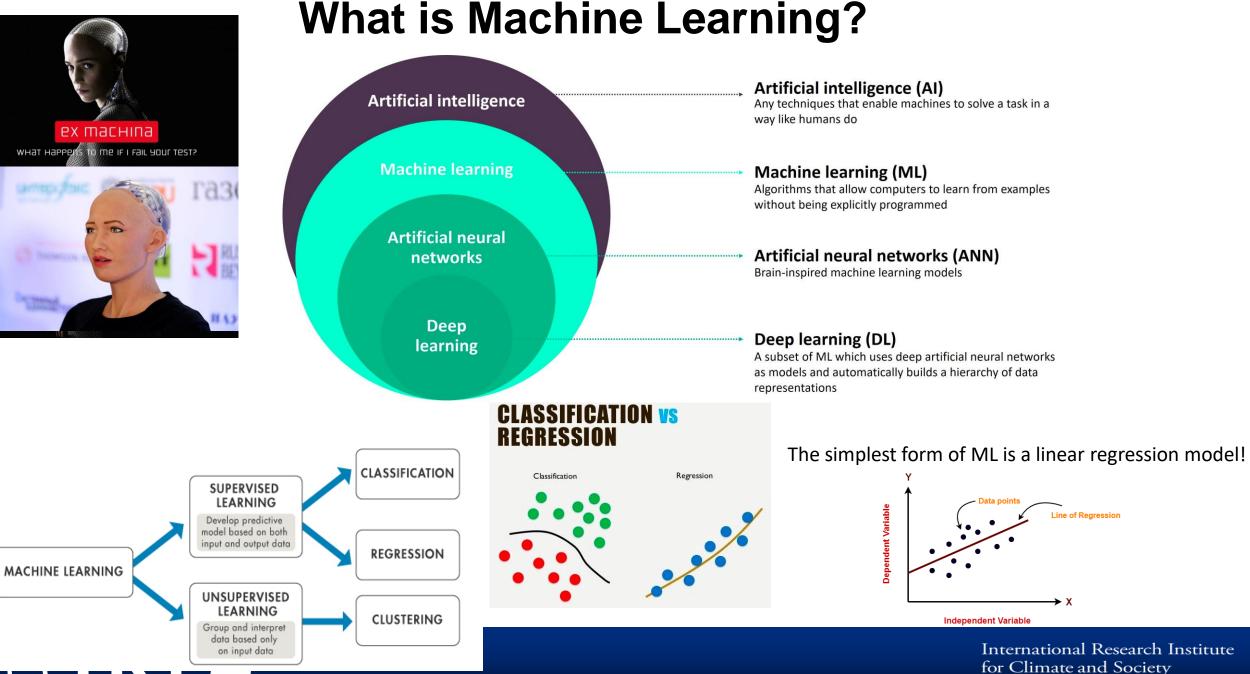
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Motivation and Goal

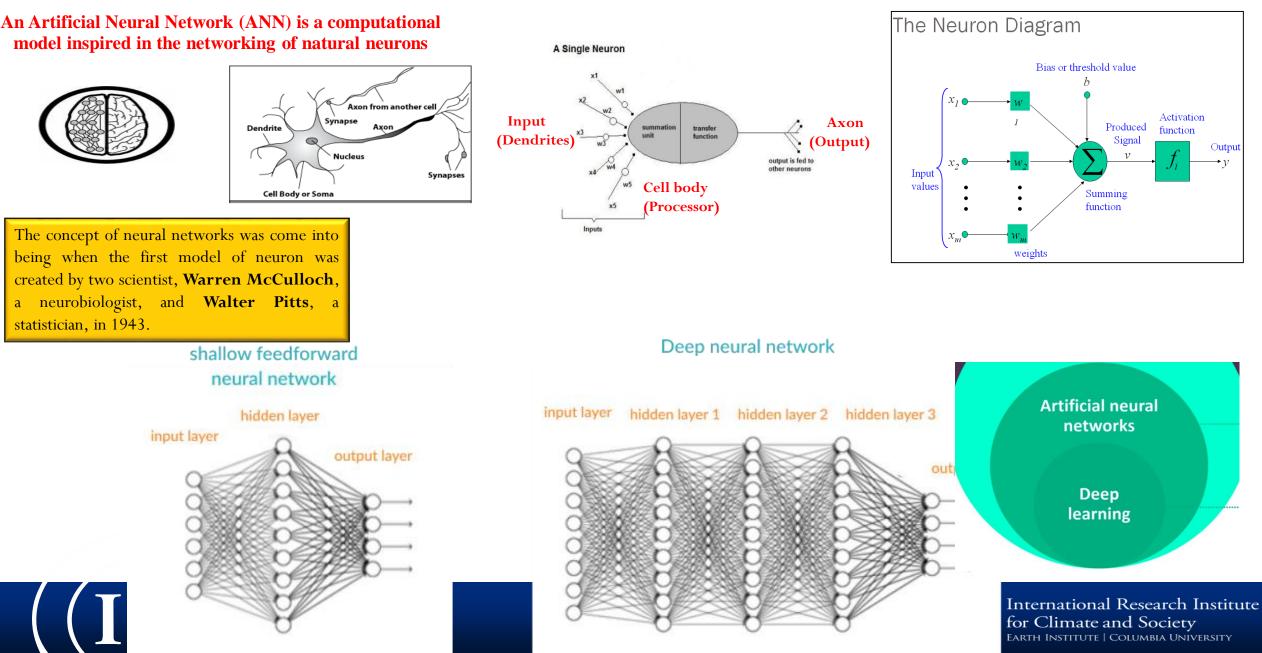
- The generation of multi-model ensemble (MME) is a well-accepted approach to improve the skill of forecasts from individual GCMs.
- There are two common approaches to make a MME, viz., combining the individual ensemble forecasts with equal weights, or weighted according to their prior performance.
- Irrespective of which combination method has been used, plethora of studies have shown that multi-model ensembles do increase prediction skill over single-model forecasting.
- Weighted MME: Mostly linear combination of GCM using multiple linear regression (MLR). (PCR, BMA).
- Does Machine Learning Based Multi-Model Ensemble Methods Add Value over Existing Methods?

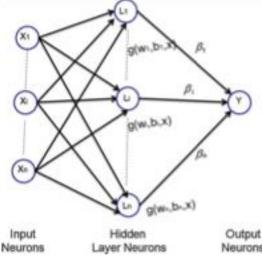




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Artificial Neural Network





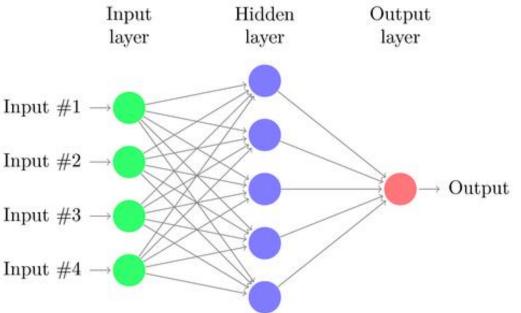
den-layer feed forward neural networks (SLFN)

dforward network (SLFN), as one of the brward neural networks, have been rom both theoretical and application Neurons arning capabilities and fault-tolerant abilities. Most of the SLFN use gradient-based learning algorithms such as the back propagation neural network



(BPNN).

* Efficiency of ANN based methods is highly dependent on appropriate tuning of their adjustable parameters, e.g., the number of hidden layers, nodes, weights and transfer function. There are also several disadvantages of traditional SLFN which includes long computation time, stopping criteria, learning rate, learning epochs, local minima, and the over-tuning problems.



Extreme Learning Machine: A "Generalized" SLFN

*****To overcome such shortcomings, recently, a novel learning algorithm for single-hidden-layer feed forward neural networks (SLFN) called extreme learning machine (ELM) has been proposed by Huang et al., (2008).

☆In the proposed algorithm, the input weights and hidden biases are randomly chosen. Randomly chosen input weights can efficiently learn distinct training examples with minimum error.

*After randomly choosing the input weights and the hidden layer biases, SLFNs can be simply considered as a linear system. The output weights which link the hidden layer to the output layer of this linear system can now be analytically determined through Moore- Penrose (MP) generalized inverse of the hidden layer output matrices.

*****The basic principle which distinguishes ELM from the traditional SLFN $h(\mathbf{x})$ is that all the parameters (input weights and hidden layer biases) are not required to be tuned.

*****This simplified approach makes ELM thousands of times faster than that of traditional SLFN. ELM also avoids many difficulties faced by gradient-based learning methods such as stopping criteria, learning rate, learning epochs, local minima, and the over- tuning problems.





"Extreme means to move beyond conventional artificial learning techniques and to move toward brain alike learning".-Huang, Nanyang Technological University,

 $f_{L}(\mathbf{x}) = \sum_{i=1}^{L} \beta_{i} G(a_{i}, b_{i}, \mathbf{x}) = \mathbf{H} \beta$ $H = \begin{bmatrix} \mathbf{h}(\mathbf{x}_{1}) \\ \vdots \\ \mathbf{h}(\mathbf{x}_{N}) \end{bmatrix} = \begin{bmatrix} h_{1}(\mathbf{x}_{1}) & \cdots & h_{L}(\mathbf{x}_{1}) \\ \vdots & \vdots & \vdots \\ h_{1}(\mathbf{x}_{N}) & \vdots & h_{L}(\mathbf{x}_{N}) \end{bmatrix}$ Salient Features

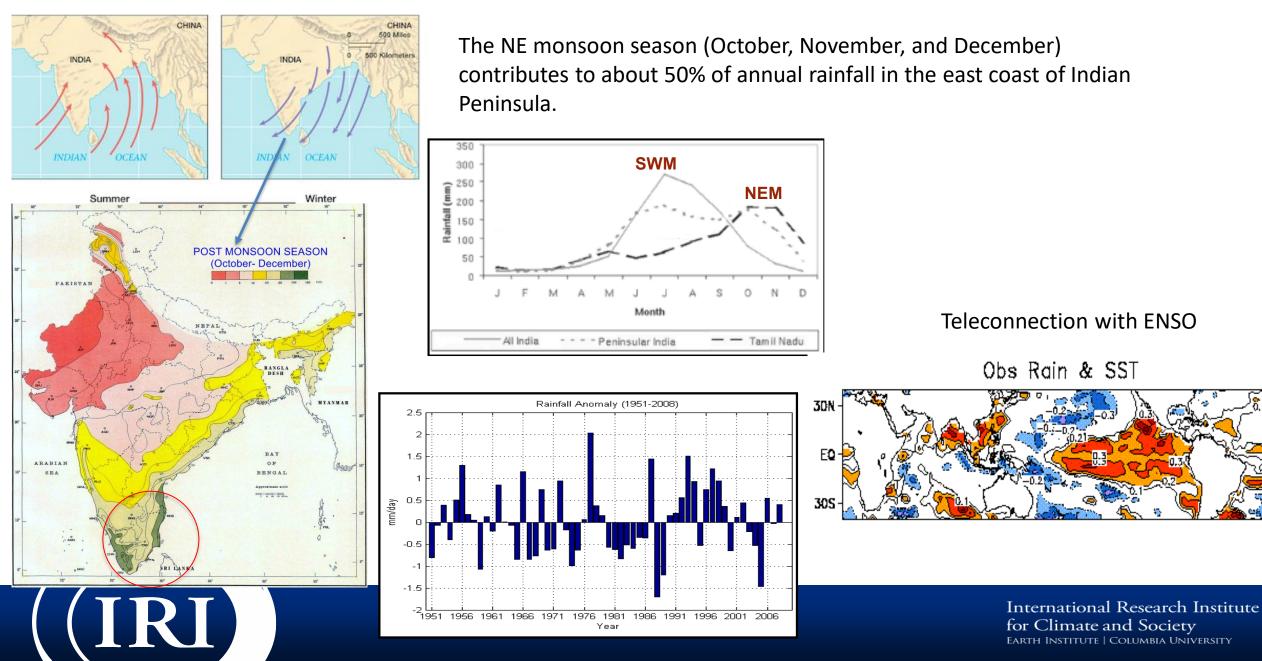
- "Simple Math is Enough." ELM is a simple tuning-free three-step algorithm.
- The learning speed of ELM is extremely fast.



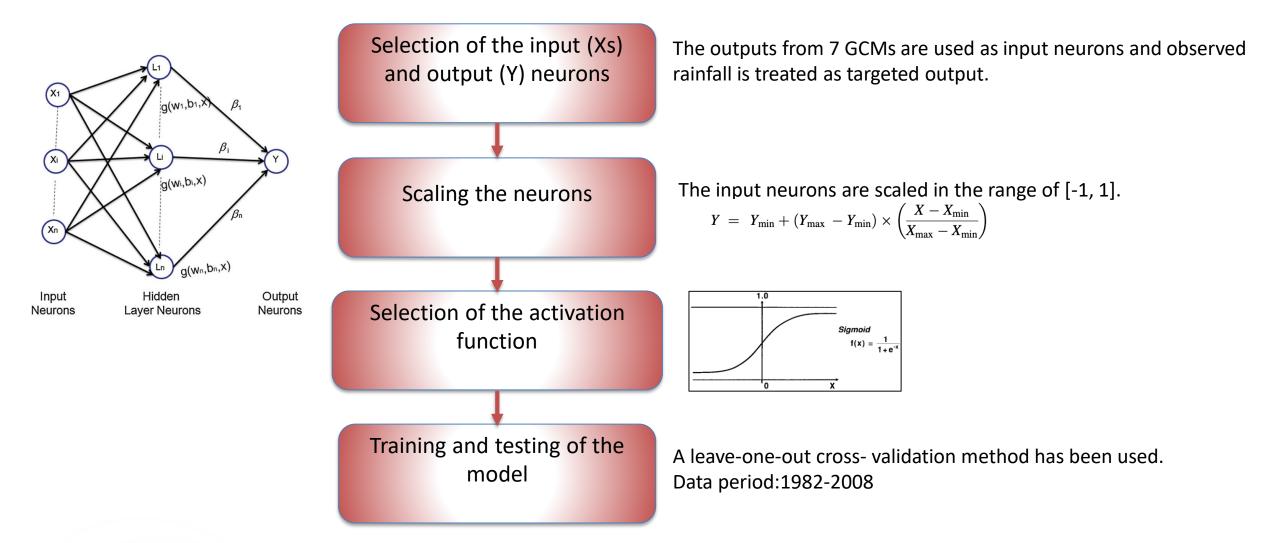
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Case study: North-East (winter) Indian Monsoon



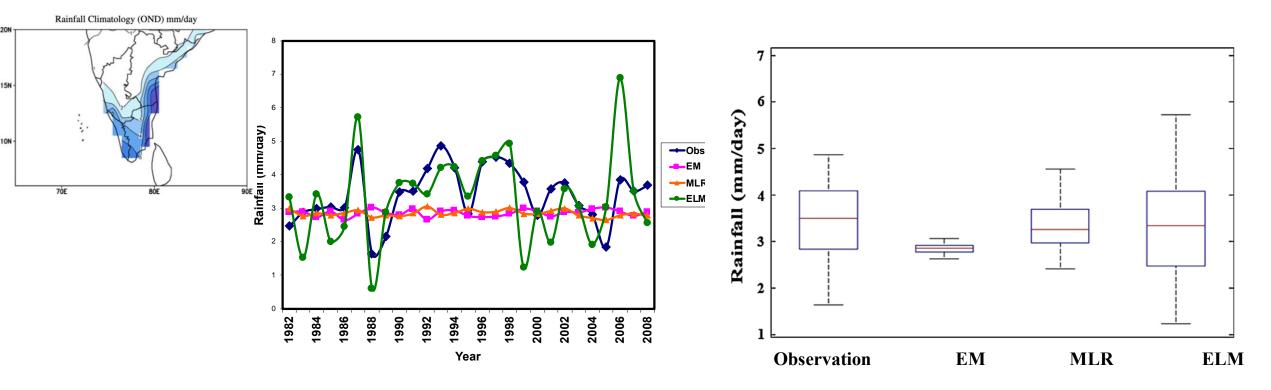
Implementation procedure of ELM for making MME



Final structure of the ELM with 7-neurons as input, 25 nodes in the hidden layer and 1 output neuron (7-25-1)



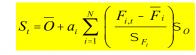
Performance of ELM-MME compare to standard MME



EM= Mean of all GCM.

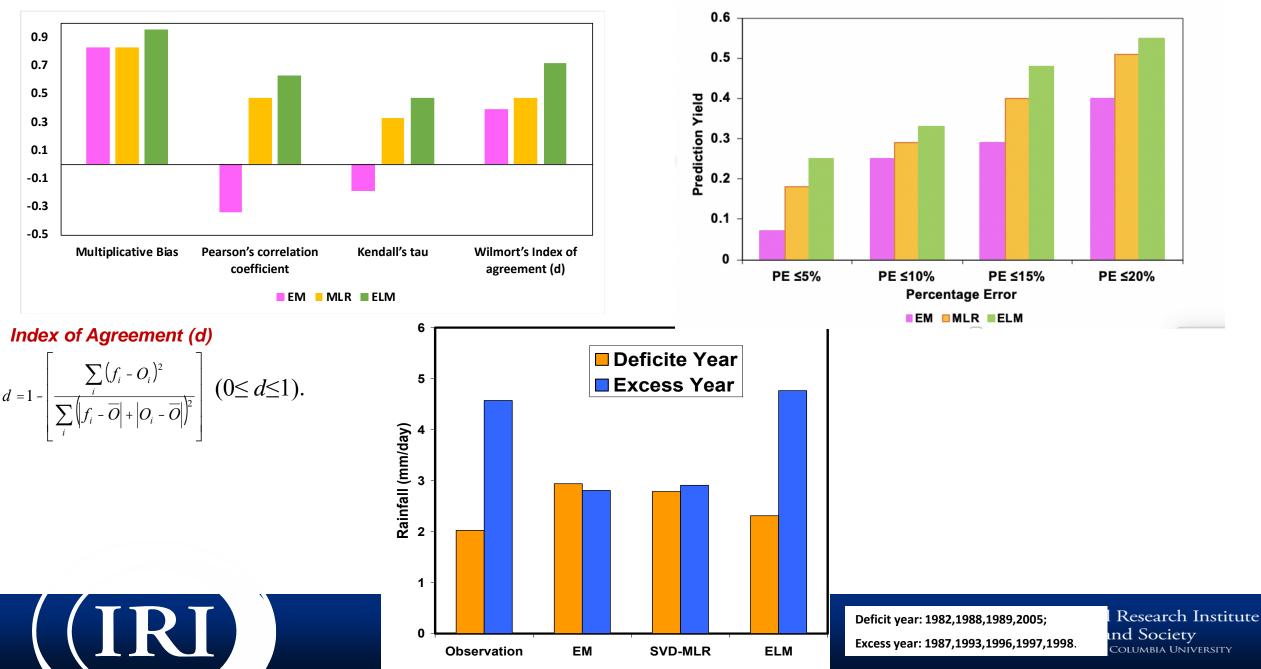
 $S_{t} = \overline{O} + \frac{1}{N} \sum_{i=1}^{N} \left(\frac{F_{i,t} - \overline{F}_{i}}{S_{F_{i}}} \right) S_{O}$

MLR= Multiple linear regression between GCMs and Observation ("Superensemble")





Performance of ELM-MME compare to standard MME



Concluding Remark

- ELM is simplified and "generalized SLFN" which make it thousands of times faster than that of traditional SLFN.
- > In ELM, parameters (input weights and hidden layer biases) need not be tuned.
- There is a significant improvement by ELM compare to existing MME methods in terms of skill scores.
- Especially, ELM capture the inter-annual variability of observed rainfall over other MME schemes.
- > ELM also capture the "extreme" year and discriminate between wet and dry year.
- Scope: Need more data to set up a more robust network for ELM.

Thank you!

Reference: Acharya N, Srivastava N.A., Panigrahi B.K. and Mohanty U.C. (2013): Artificial Neural Network based Multi-model ensemble to improve prediction of northeast monsoon rainfall over South Peninsular India: an application of Extreme Learning Machine. *Climate Dynamics* DOI: 10.1007/s00382-013-1942-2.

Any Feedback?

