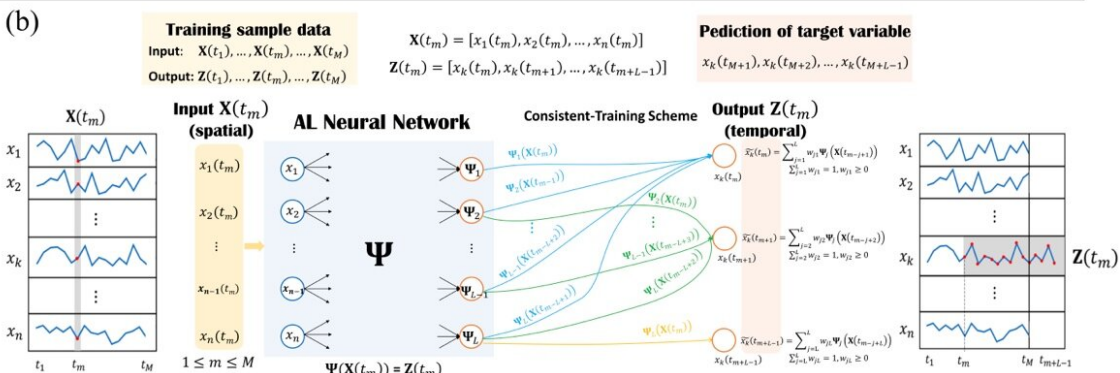
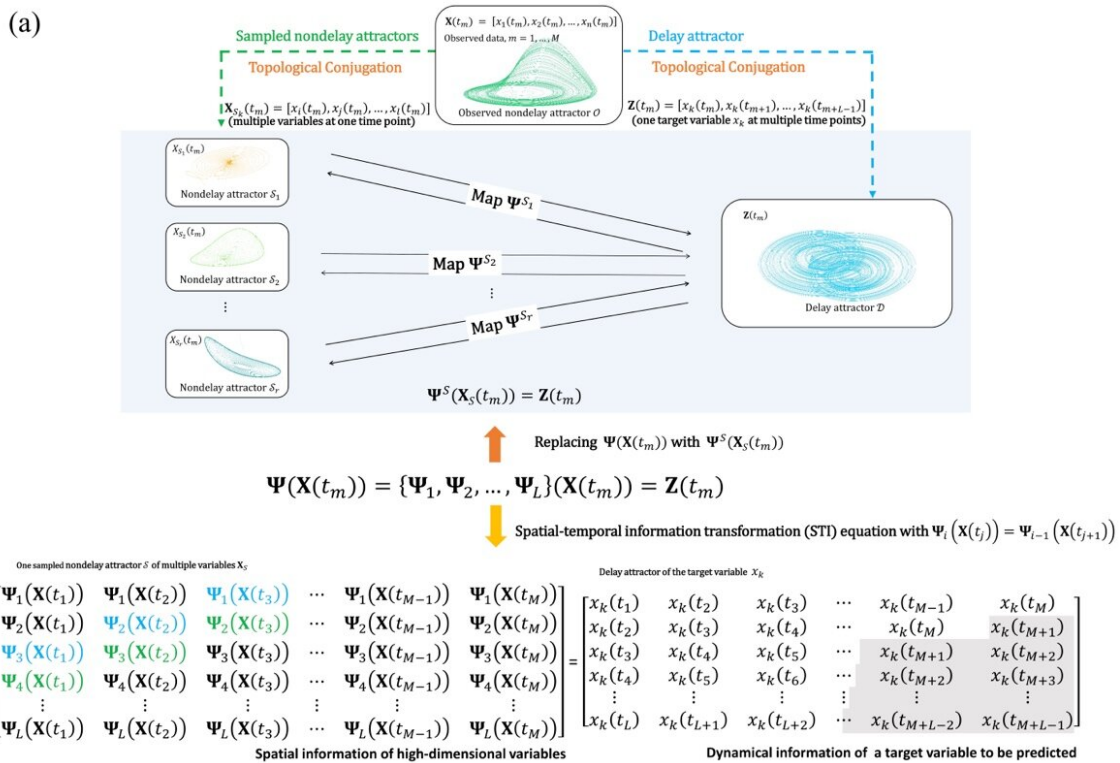


# Future dynamics prediction from short-term time series by anticipated learning machine

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(a) The general principle of Anticipated Learning Machine (ALM). The

observed attractor, a delay attractor and sampled nondelay attractors are all topologically conjugate with each other. Each sampled nondelay attractor preserves the dynamical information of the system in different ways. By integrating the information contained in these sampled nondelay attractors, we could find an accurate one-to-one map even under noise deterioration.(b) Anticipated Learning Machine. For each future value, those maps are co-trained into a unified map  $\Psi$ . When the maps are trained, the weighted sum is used as the prediction. The predicted value is then used as the label when training other maps to predict the next time point. Clearly, ALM  $\Psi$  transforms spatial input  $X(t_m)$  to temporal output  $Z(t_m)$  at each point  $t_m$ . Credit: ©Science China Press

Making an accurate prediction based on observed data, in particular from short-term time series, is of much concern in various disciplines—from molecular biology, neuroscience, geoscience, and economics to atmospheric sciences—due to either data availability or time-variant non-stationarity. However, most of existing methods require sufficiently long measurements of time series or a large number of samples, and there is no effective method available for prediction with short-term time-series because of lack of information.

To address this issue, Prof. Chen Luonan (Institute of Biochemistry and Cell Biology, Chinese Academy of Sciences) with Dr. Chen Chuan (Sun Yat-sen University), Prof. Ma Huanfei (Soochow University) and Prof. Aihara Kazuyuki (University of Tokyo) proposed a new dynamics-based data-driven method, anticipated learning machine (ALM), for achieving precise future-state predictions based on short-term but high-dimensional data. ALM is a multi-layered [neural network](#) where high-dimensional variables are taken as input neurons (multiple variables but at a single time point) but a target variable is taken as output neurons (single variable but at multiple time points). In this way, ALM is able to transform the recent correlation/spatial information of high-dimensional variables to future dynamical/temporal information of any target

variable, i.e. by spatial-temporal information transformation (STI) equations.

Specifically, ALM can be well trained to represent the randomly distributed embedding (RDE) map for STI equations by a large number of the generated training samples with the Dropout scheme and the proposed consistent-training scheme, thus predicting the target variable in an accurate and robust manner, even from short-term data. Extensive experiments on the short-term high-dimensional data from both synthetic and real-world systems demonstrated significantly superior performances of ALM over existing methods.

Compared with traditional neural networks (or other machine learning approaches) which excavate the historical statistics of the original high-dimensional system and thus require a large number of samples, ALM efficiently and robustly reconstructs its dynamics even with a small number of samples by constraining to a low-dimension space which is actually an inherent property of such a dissipative system. Based on nonlinear dynamics to transform the spatial [information](#) of the all measured high-dimensional variables into the temporal evolution of the target variable by learning the STI equations, ALM open a new path for dynamics-based machine learning or "intelligent" anticipated learning.

"How to consider the strong nonlinearity or/and stochasticity of the dynamical systems also with the observed noisy data, and further how to make more in-depth [theoretical analysis](#) and further develop an appropriate framework taking these issues into consideration remain an open and interesting problem in future," state the authors.

**More information:** Chuan Chen et al, Predicting future dynamics from short-term time series by anticipated learning machine, *National Science Review* (2020). [DOI: 10.1093/nsr/nwaa025](https://doi.org/10.1093/nsr/nwaa025)

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