The impact of learning strategies for interactive ensembles in the presence of unresolved scales[1]

1. Supermodels (SUMOs): interactive ensembles of existing models
- Proposal to improve climate modelling[2]
- Assumption: models are good but imperfect
- Model combination for improvement
- Alternative to conventional noninteractive ensemble methods
- Supermodel = Ensemble of dynamically coupled models

Individual model dynamics
\[ \dot{x}_i = f_i(x_i) \]
(This poster) SUMO coupling by weighted averaging
\[ \dot{x} = \sum w_i f_i(x) \]

SUMO couplings need to be optimized
e.g. by minimizing short term prediction error \( E \) → Very successful in simulations, good attractors[2]

- However: perfect model class scenario
- Unrealistic assumption
- What are the consequences
- What are alternative training methods

2. Perfect model class scenario
- Assumed Ground Truth (GT) in same model class as imperfect models (IMs)
- So IMs have imperfect model parameters
- But in the same perfect model class
- Example: Lorenz 63 experiment (L63) below [2]

Standard L63

Top row, black: IMPERFECT MODELS - L63 with perturbed parameters
Right, black: SUMO
Grey: GROUND TRUTH - L63 with standard parameters

3. Imperfect model class scenario
- GT is more complex than IMs (unresolved scales)
- Example: Chaotically driven L63, see below
- Short term prediction learning \( \rightarrow \) wrong attractor
- Remedied by attractor learning

Chaotically driven L63

4. Bayesian optimization
- For optimization of expensive cost functions
- Models cost function as well uncertainty
- Using Gaussian process regression
- Selects new point based on expected improvement

5. QG3 Model
- Spectral three-level quasi-geostrophic model
- Simulating winter-time atmosphere in the Northern hemisphere (QG3), from [3]
- GT: T42 resolution model
- IMs: T21 resolution model with perturbed parameters

SUMO equations for potential vorticity (PV)

\[ \frac{\partial}{\partial t} [ \varphi + D(\varphi, \psi, \mu)] + \nabla \cdot [ \nabla (\varphi + D(\varphi, \psi, \mu))] = 0 \]

SUMOs optimized for \( E \) and \( U \), where

\[ L^2 = [\sigma_1 - \sigma_0]^2 \]

6. CONCLUSIONS
- Nonlinear dynamical systems: reducing error on the level of short term prediction does not necessarily lead to improved climate properties
- Attractor learning may needed (Bayesian optimization)
- The cost function that is minimized may have a strong influence on the result
- Be careful with perfect model scenario simulations, they can give over-optimistic results

References