

**Reduced-order manifold models:** lower computational cost by projecting the thermochemical state onto a manifold with  $N_\xi \ll N_S$  dimensions. Both physics-based (Flamelet Generated Manifolds, FGM) and data-driven (Principal Component Analysis, PCA) approaches share the same three major steps:

**Definition of manifold variables**

$$\xi_i = W_{ij} Y_j$$



**Mapping to output variables – often using a neural network**

$$\phi_k = (Y_j, T, \omega_j, D, \mu, \dots) = F(\xi_i)$$

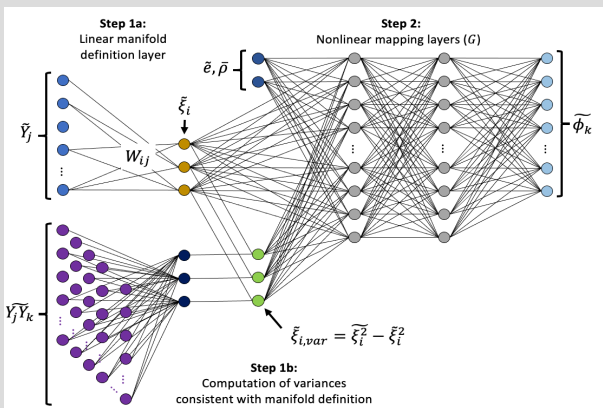


**LES closure of filtered quantities**

$$\tilde{\phi}_k = \tilde{F}(\xi_i) = G(\xi_i, \xi_{i,var})$$

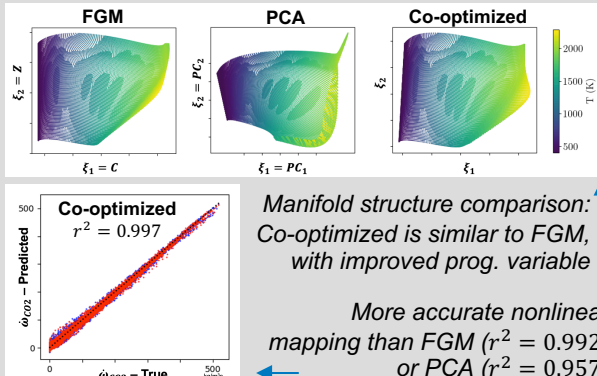
**Co-optimized Machine-Learned Manifolds Approach:** extend the neural network used for nonlinear mapping to allow simultaneous learning for all three steps

## Proposed Neural Network Structure



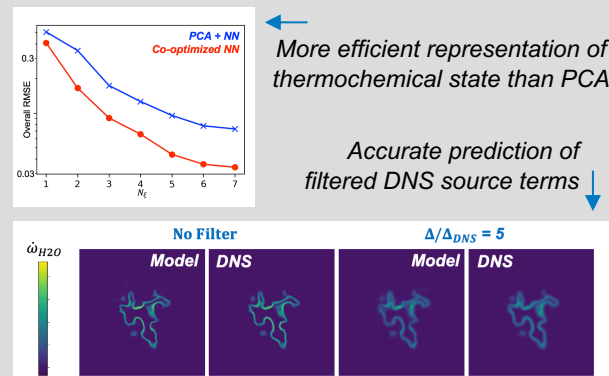
## Case 1: 1D Premixed Flame Data

CH<sub>4</sub> (DRM19 mech.),  $\phi = 0.5-1.5$ , 1 atm,  $T_0 = 400$  K



## Case 2: Jet-A Ignition Kernel DNS Data

Data from Krisman et al., CNF, 2021



**The proposed approach can flexibly incorporate thermochemical data from any source, yielding optimized versions of physics-based models in the appropriate limits, but also enabling accurate predictions by including additional data when physics-based manifold descriptions are not available**