System Design as a Mechanism for the Generalization of Learning Algorithms

Dr. Peter Beling and Tyler Cody

Research Task / Overview

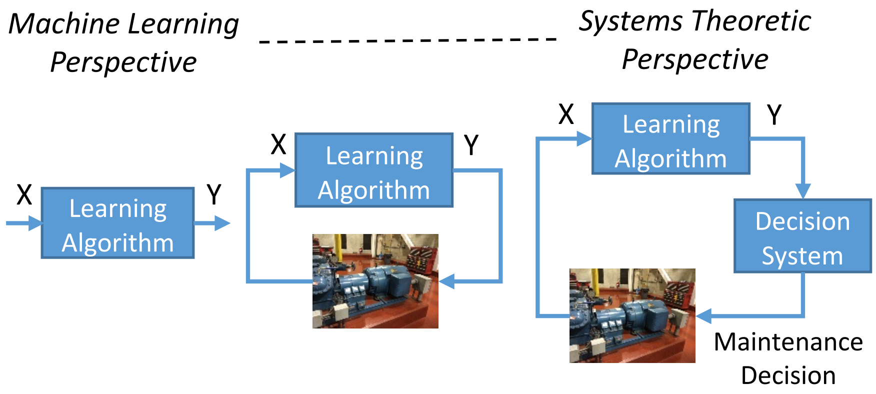
Machine learning (ML) has moved beyond being a research field to being a workable approach for building autonomous functions into systems. A key challenge in designing learning systems is *generalization*, wherein a learning system can perform its functions outside of its training environment, in operational environments that vary between instances of systems, and evolve over time.

Systems theory provides an approach for modeling such lifecycle challenges faced by ML systems in a framework naturally rooted in systems design and analysis. It is a mathematical superstructure for learning that allows for learning algorithms to be formally studied in the context of the systems within which they operate, and the operationalization of resulting theories can inform the design and operation of resulting ML systems.

Data & Analysis

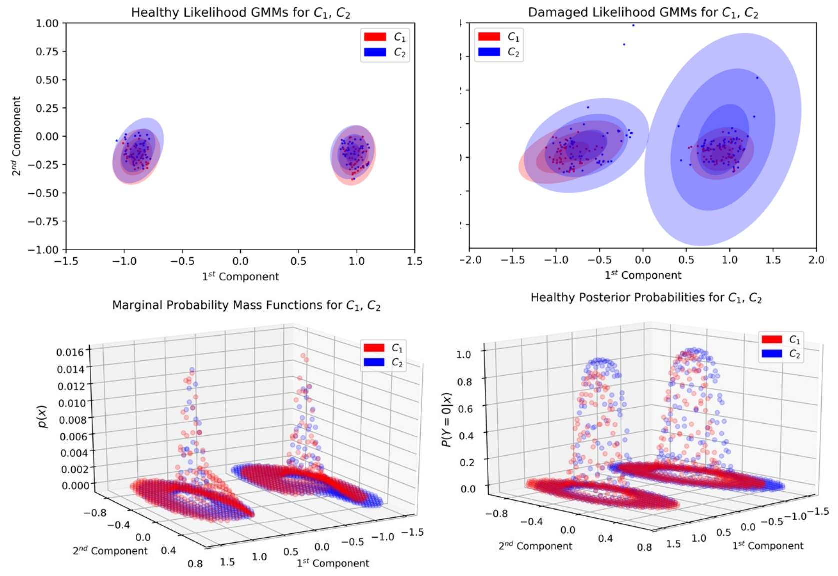
We take a perspective different than traditional machine learning; we consider the learning problem to be related to the structural and behavioral nature of systems, not just the learning algorithms themselves.

Consider the problem of generalizing a health monitoring algorithm across actuator system rebuilds. We can study the distributional change associated with a particular rebuild procedure. C_1 and C_2 are the actuator before and after a rebuild, respectively.



We can perform *a Bayesian characterization of transfer distance* using the Hellinger distance metric to compare the components of Bayes theorem:

$$P(Y=0|X=x) = \frac{p(X=x|Y=0)P(Y=y)}{p(X=x)}$$



By mathematically studying this distributional change, we can create an expected model of change for use in model-based learning approaches. Furthermore, by eliciting trade-offs between rebuild procedures and the resulting generalization problems we establish a mechanism for generalization via system design.

Goals & Objectives

Our high level goal is to contribute to the development of a principled discipline of AI systems engineering by:

- Constructing systems theoretic formalizations of learning processes
- Embedding formalizations in the context of broader systems theory
- Operationalizing theory with applications in applied ML

We plan to iterate through this process with a focus on system design, and in doing so, deliver engineering methodologies grounded in mathematical theory with accompanying real-world case studies.

Methodology

A learning algorithm A is a map,

$$A: D \to f^{\theta}$$

from data D to a learned algorithm parameterized by θ,

$$f^{\theta}: X \to Y$$

from input X to output Y.

Given an evaluation function,

$$v: f^{\theta} \to \mathbb{R}$$

that maps from a learned algorithm to the reals, and a real threshold ϵ, we are interested in identifying the neighborhood,

$$N = \{P(X,Y) | v(f^{\theta}) \geq \epsilon\}$$

of probability distributions where the learned algorithm f^{θ} performs satisfactorily according to v.

In combination with knowledge of the system behavior, captured by the random process,

$$R(X,Y) = \{P_t(X,Y) | t = 1, \ldots, T\}$$

from time $t=1$ to $t=T$, we can study the relationship between the evolution of system behavior and the neighborhood of behaviors the learning algorithm is performant under.

Under this model of learning, system design influences learning through $R(X,Y)$.

Conclusions & Future Research

- A systems theoretic approach to lifecycle AI challenges has utility in systems design and analysis
- It considers a broader problem than traditionally considered by the machine learning community without sacrificing formalism
- We next intend to show how models of random processes undergone by systems can lead to principled design and operational decisions

Contacts & Selected Publications

Peter Beling – beling@virginia.edu
Tyler Cody – tmc4dk@virginia.edu

Tyler Cody, Stephen Adams, Peter A. Beling. “A Systems Theoretic Perspective on Transfer Learning.” IEEE SysCon 2019.

Tyler Cody, et. al. “Transferring Random Samples in Actuator Systems for Binary Damage Detection.” IEEE PHM 2019.