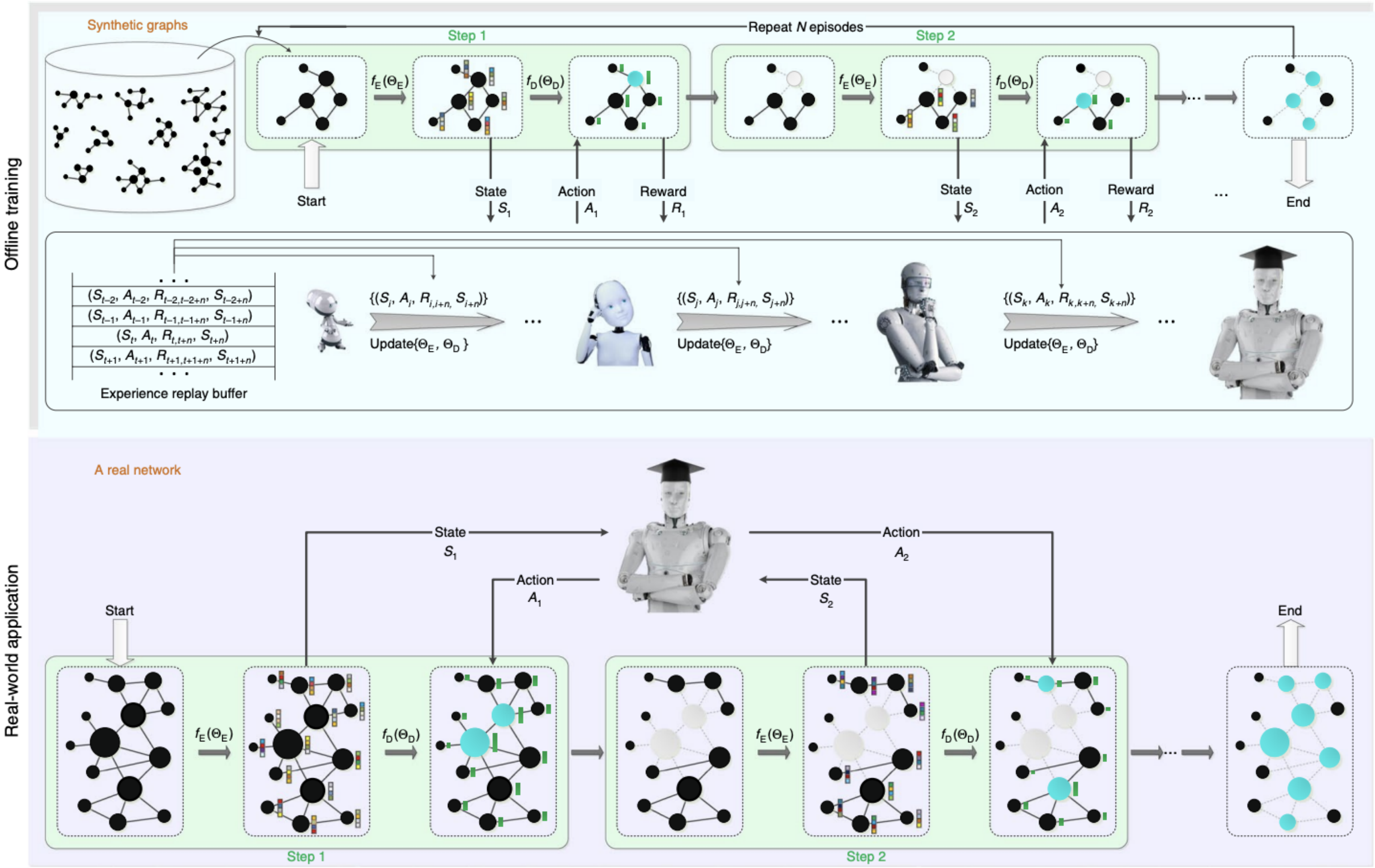
Deep reinforcement learning



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Article | Published: 25 May 2020

Finding key players in complex networks through deep reinforcement learning

Changjun Fan, Li Zeng, Yizhou Sun & Yang-Yu Liu

Nature Machine Intelligence 2, 317–324 (2020) | Cite this article

Abstract

Finding an optimal set of nodes, called key players, whose activation (or removal) would maximally enhance (or degrade) a certain network functionality, is a fundamental class of problems in network science. Potential applications include network immunization, epidemic control, drug design and viral marketing. Due to their general NP-hard nature, these problems typically cannot be solved by exact algorithms with polynomial time complexity. Many approximate and heuristic strategies have been proposed to deal with specific application scenarios. Yet, we still lack a unified framework to efficiently solve this class of problems. Here, we introduce a deep reinforcement learning framework FINDER, which can be trained purely on small synthetic networks generated by toy models and then applied to a wide spectrum of application scenarios. Extensive experiments under various problem settings demonstrate that FINDER significantly outperforms existing methods in terms of solution quality. Moreover, it is several orders of magnitude faster than existing methods for large networks. The presented framework opens up a new direction of using deep learning techniques to understand the organizing principle of complex networks, which enables us to design more robust networks against both attacks and failures.

https://www.nature.com/articles/s42256-020-0177-2

Data driven control for complex networks

nature communications

Article | Open access | Published: 03 March 2021

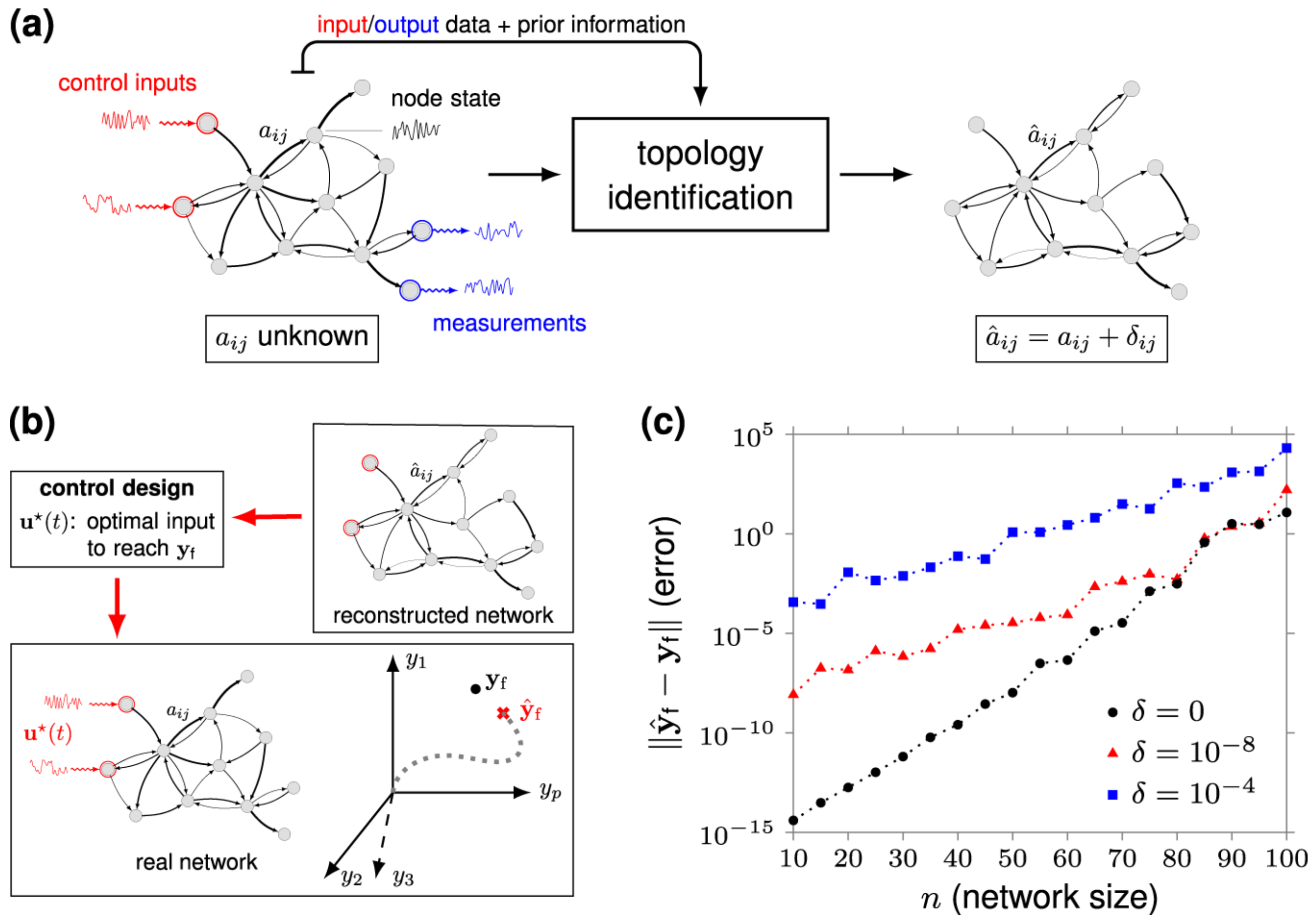
Data-driven control of complex networks

Giacomo Baggio, Danielle S. Bassett & Fabio Pasqualetti ✉

Nature Communications **12**, Article number: 1429 (2021) | Cite this article

Abstract

Our ability to manipulate the behavior of complex networks depends on the design of efficient control algorithms and, critically, on the availability of an accurate and tractable model of the network dynamics. While the design of control algorithms for network systems has seen notable advances in the past few years, knowledge of the network dynamics is a ubiquitous assumption that is difficult to satisfy in practice. In this paper we overcome this limitation, and develop a data-driven framework to control a complex network optimally and without any knowledge of the network dynamics. Our optimal controls are constructed using a finite set of data, where the unknown network is stimulated with arbitrary and possibly random inputs. Although our controls are provably correct for networks with linear dynamics, we also characterize their performance against noisy data and in the presence of nonlinear dynamics, as they arise in power grid and brain networks.



https://www.nature.com/articles/s41467-021-21554-0/figures/1

Controlling complex networks review

nature reviews physics

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Perspective | Published: 24 March 2023

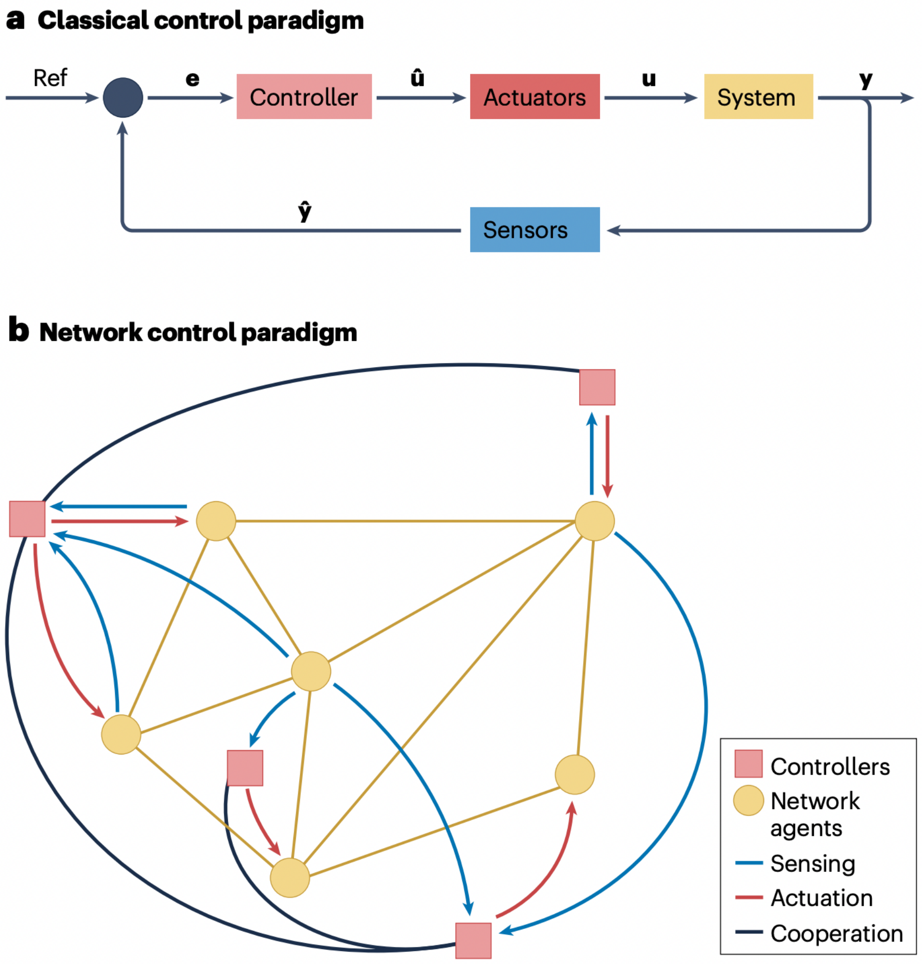
Controlling complex networks with complex nodes

Raissa M. D'Souza, Mario di Bernardo & Yang-Yu Liu

Nature Reviews Physics 5, 250–262 (2023) | Cite this article

Abstract

Real-world networks often consist of millions of heterogenous elements that interact at multiple timescales and length scales. The fields of statistical physics and control theory both contribute different perspectives for understanding, modelling and controlling these systems. To address real-world systems, more interaction between these fields and integration of new paradigms such as heterogeneity and multiple levels of representation will be necessary. It may be possible to expand models from statistical physics to integrate the notion of feedback (both positive and negative) and to extend control theory formulations to more mesoscopic analysis over averages of collections of degrees of freedom. There is also the need to integrate theoretical models, machine learning and data-driven control methods. We review recent progress and identify opportunities to help advance understanding and control of real-world systems from oscillator networks and social networks to biological and technological networks.



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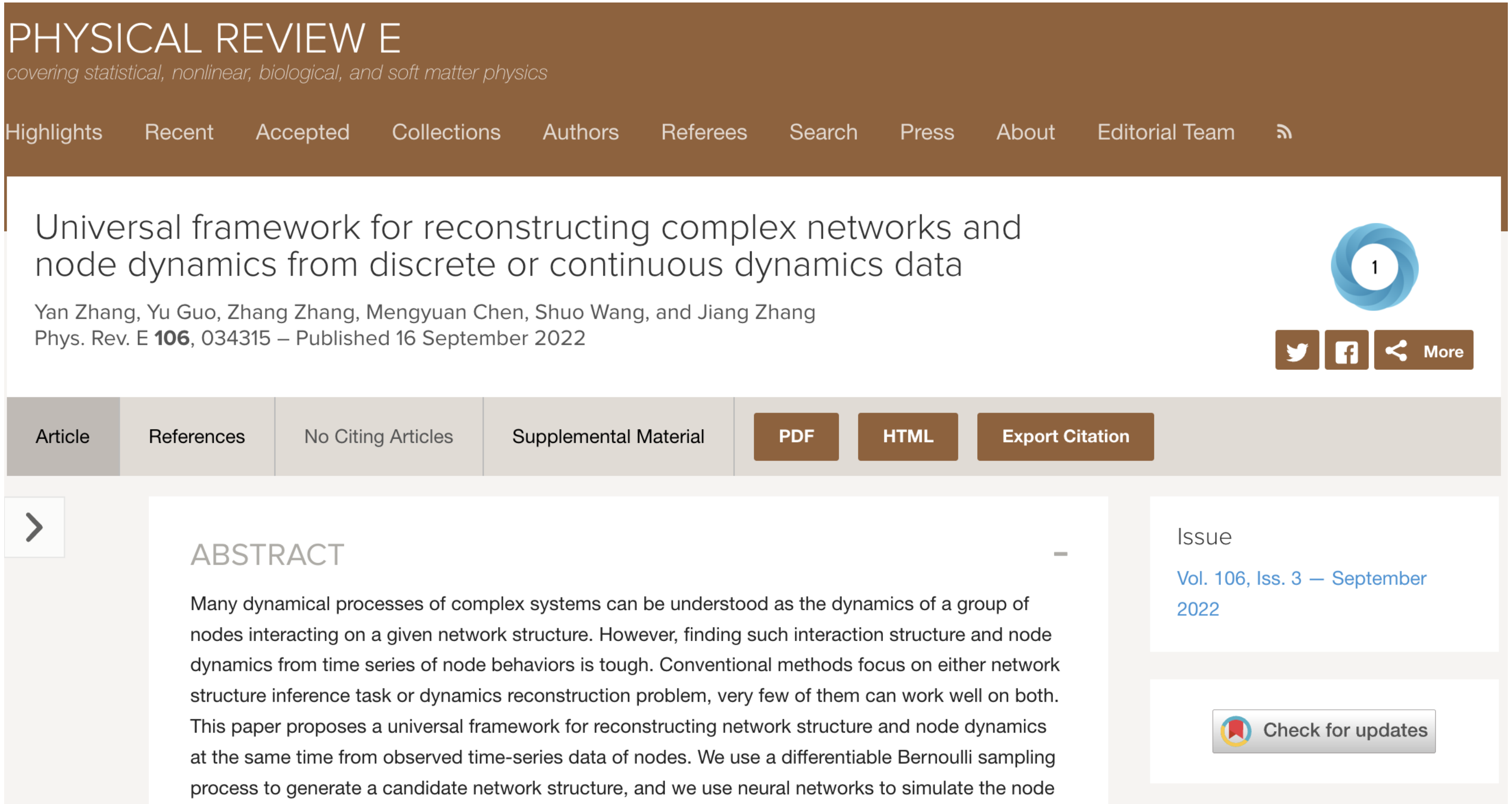

PHYSICAL REVIEW E
covering statistical, nonlinear, biological, and soft matter physics

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Universal framework for reconstructing complex networks and node dynamics from discrete or continuous dynamics data

Yan Zhang, Yu Guo, Zhang Zhang, Mengyuan Chen, Shuo Wang, and Jiang Zhang
Phys. Rev. E **106**, 034315 – Published 16 September 2022

Article | References | No Citing Articles | Supplemental Material | PDF | HTML | Export Citation

ABSTRACT

Many dynamical processes of complex systems can be understood as the dynamics of a group of nodes interacting on a given network structure. However, finding such interaction structure and node dynamics from time series of node behaviors is tough. Conventional methods focus on either network structure inference task or dynamics reconstruction problem, very few of them can work well on both. This paper proposes a universal framework for reconstructing network structure and node dynamics at the same time from observed time-series data of nodes. We use a differentiable Bernoulli sampling process to generate a candidate network structure, and we use neural networks to simulate the node

Issue

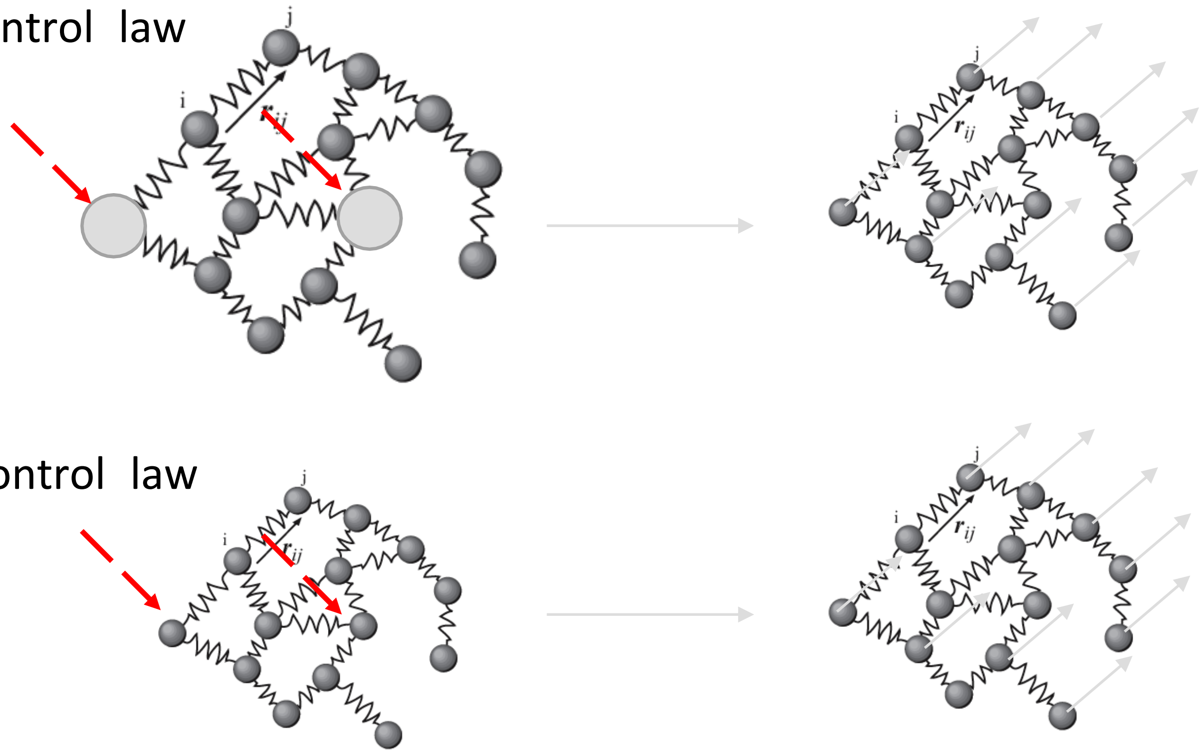
Vol. 106, Iss. 3 — September 2022

https://journals.aps.org/pre/abstract/10.1103/PhysRevE.106.034315

Automated Modelling of Complex Systems

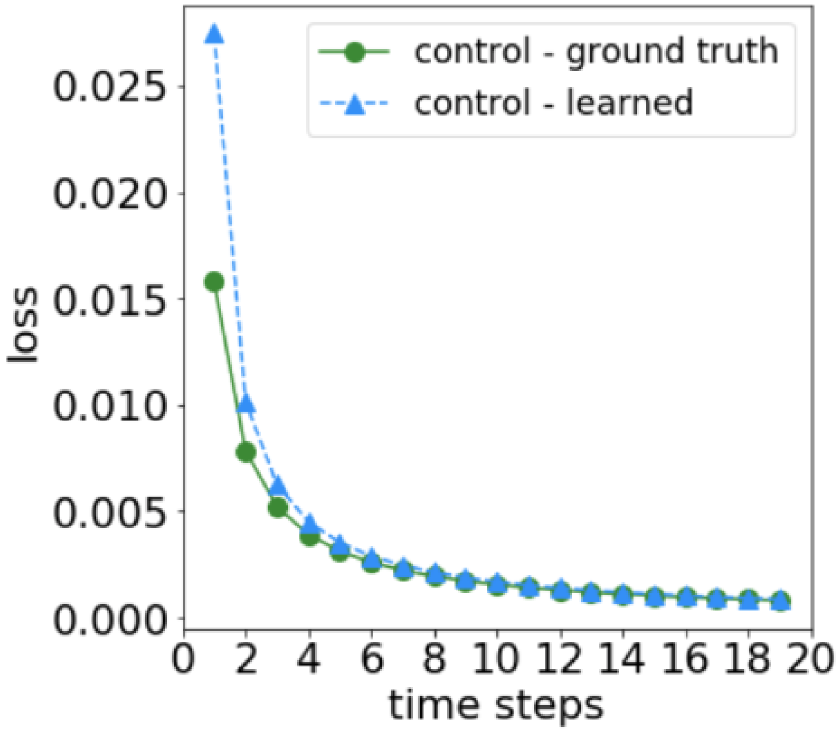
Control law

Control law



Learned

Real



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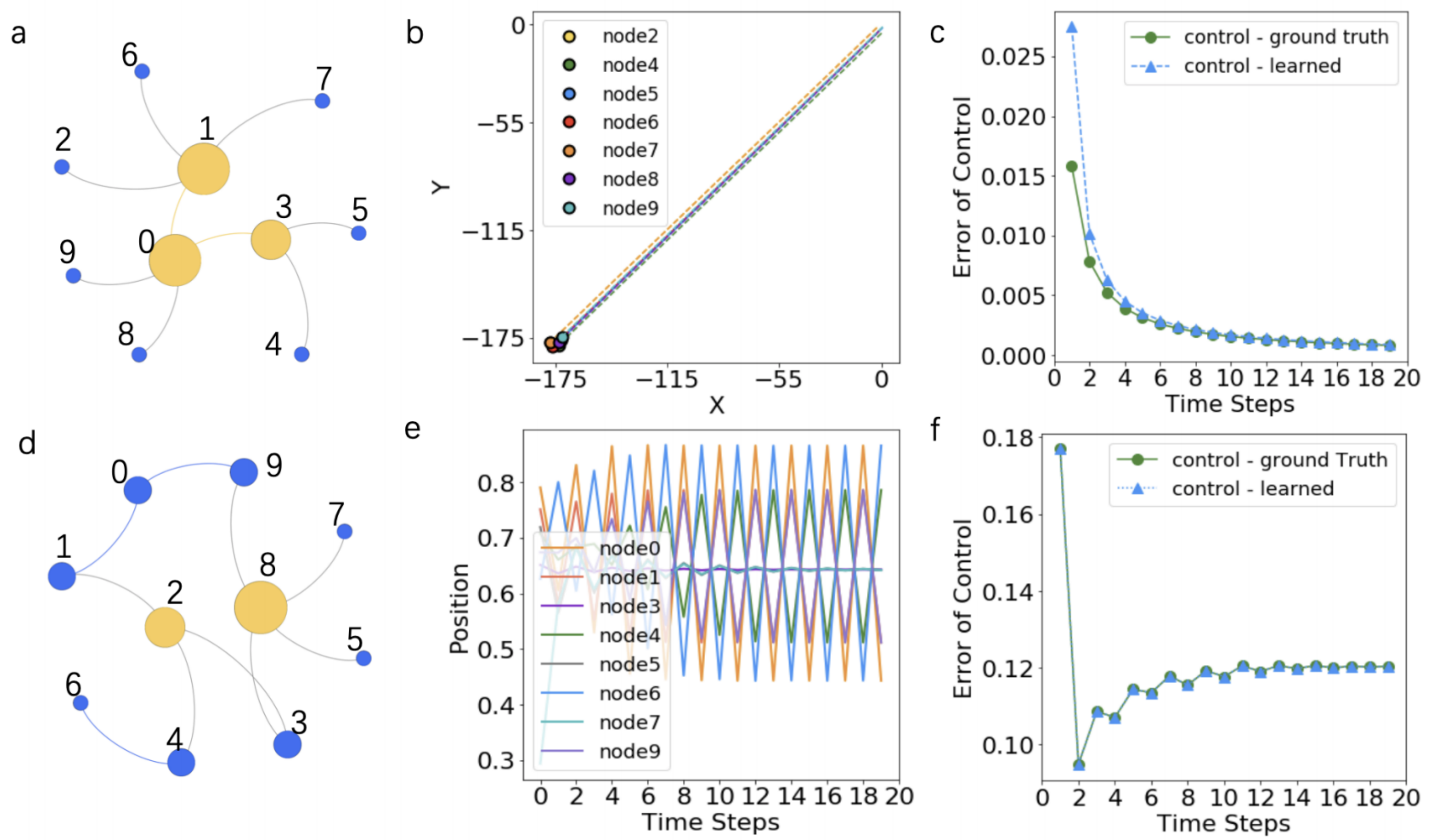
Automated Modelling of Complex Systems



https://journals.aps.org/pre/abstract/10.1103/PhysRevE.106.034315

Model Predictive Complex System Control from Observational and Interventional Data

Muyun Mou,[1, a)] Yu Guo,[2] Fanming Luo,[3] Yang Yu,[3] and Jiang Zhang[1]
[1)] *School of Systems Science, Beijing Normal University, Beijing 100875, China*
[2)] *School of Reliability and Systems Engineering, Beihang University, Beijing 100875, China*
[3)] *National Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210008, China*

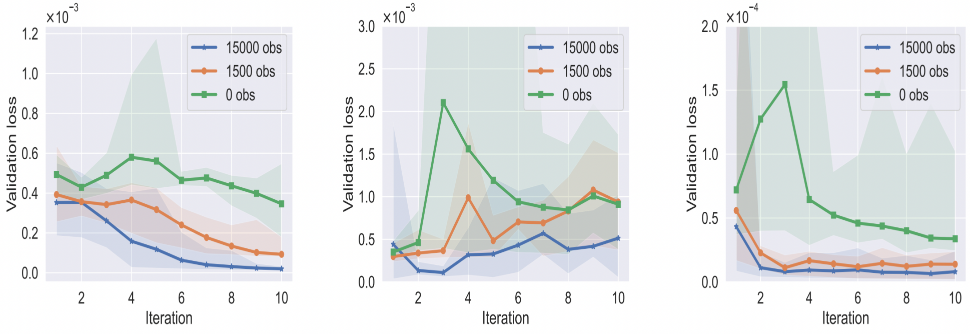
(*Electronic mail: zhangjiang@bnu.edu.cn)

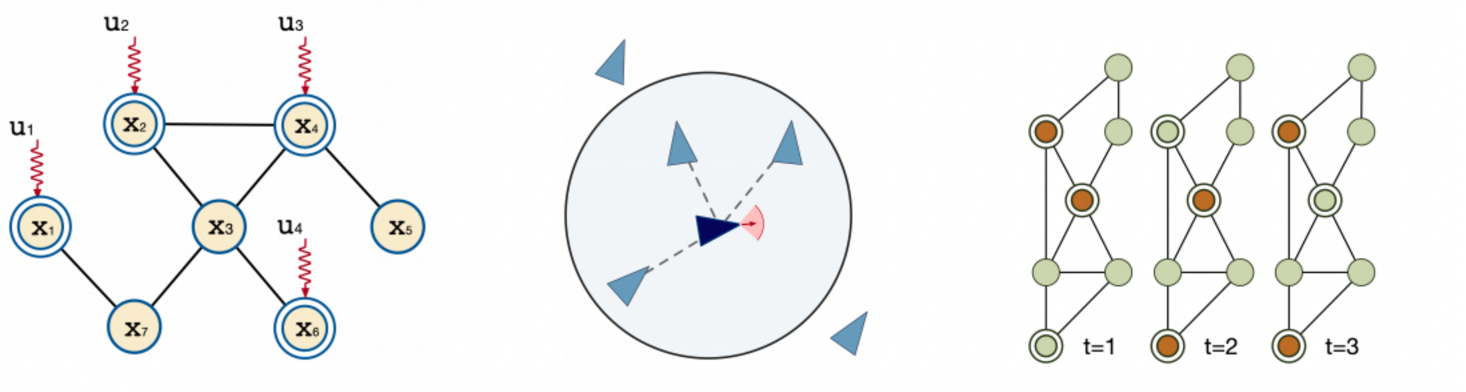
(Dated: 30 March 2024)

Complex systems, characterized by intricate interactions among myriad entities, give rise to emergent behaviors whose modeling and control are of utmost significance. This paper discusses the challenges of modeling and controlling these systems in a data-driven manner, especially when there is abundant observational data but the cost of intervention is high. Traditional methods rely on precise dynamical models or require extensive intervention data, which fall short when dealing with real-world complexity. To bridge this gap, we introduce a two-stage Model Predictive Complex System Control (MPCSC) framework, comprising an offline pre-training phase that leverages abundant observational data for spontaneous evolution dynamics and an online fine-tuning phase that uses Model Predictive Control for intervention actions. To address the high-dimensional nature of the state-action space in complex systems, we propose a novel approach employing action-extended Graph Neural Networks to model the Markov decision process of complex systems and design a hierarchical action space for learning intervention actions. This approach demonstrates impressive performance across diverse complex system control problems, including the Boids model for collective behavior, the Kuramoto model for network synchronization, and the SIS metapopulation model for epidemic spreading. It offers accelerated convergence, robust generalization, and reduced intervention costs. This work provides valuable insights into the control of complex systems with high-dimensional state-action space and limited intervention data, offering promising applications for real-world challenges.

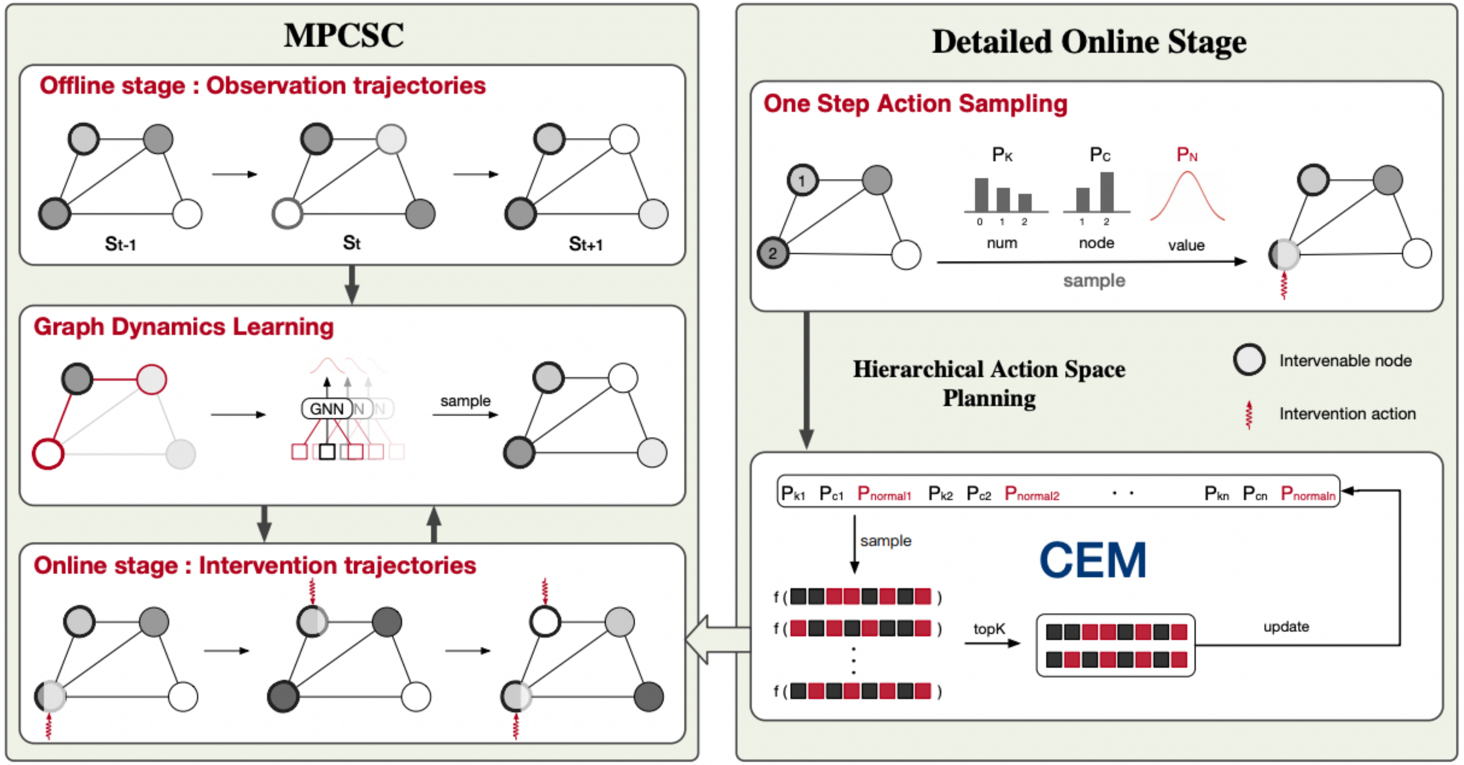
The development of artificial intelligence technology has led to a trend in learning the control strategy of complex systems from data. However, effective learning of control strategy often requires a large amount of intervention data, which can be costly and challenging for complex systems in real-world scenarios. Therefore, it is of great significance to be able to simultaneously combine a large amount of low-cost observational data with a small amount of intervention data to learn the control strategy of

amples including brain neural networks, flocks of birds, transportation networks, and epidemic spreading. Investigating the modeling and control of complex systems holds significant importance in comprehending and guiding their behaviors. In the traditional domain of complex systems, the micro-level interactions of individual components are modeled based on domain knowledge[2–4], and optimization control methods are studied using the established models[5]. However, crafting a comprehensive model for real-world complex systems is both

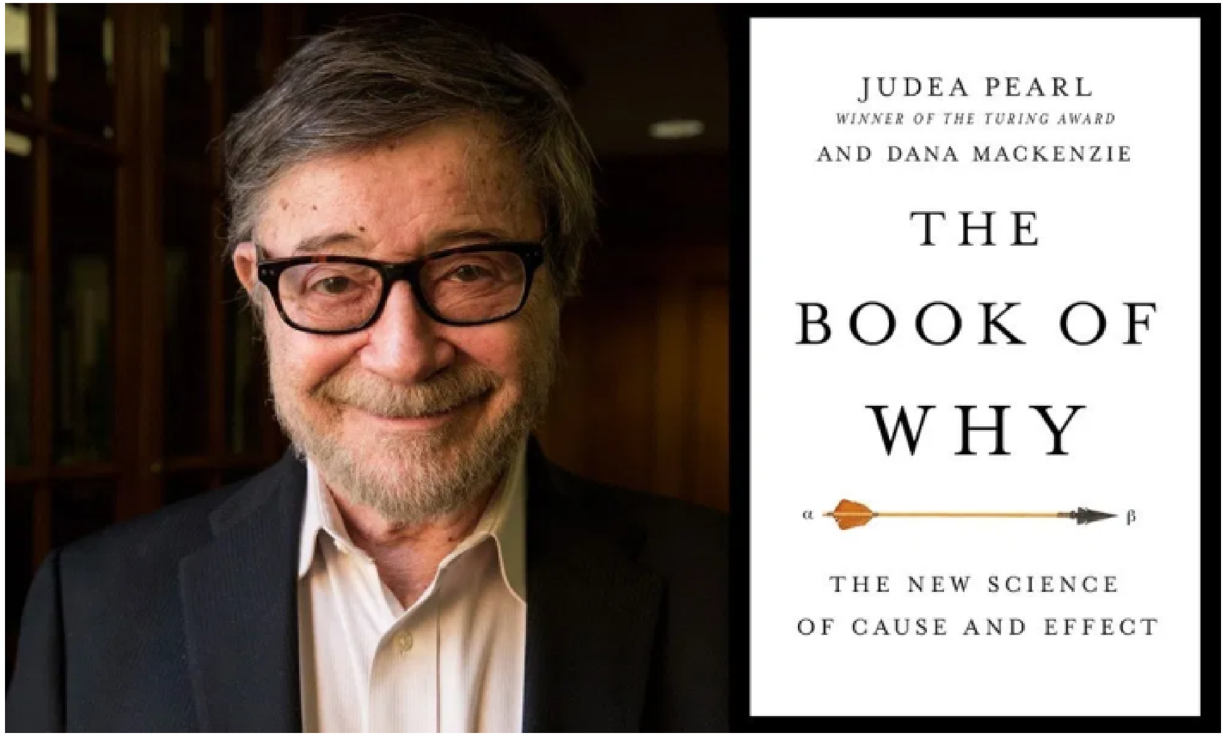


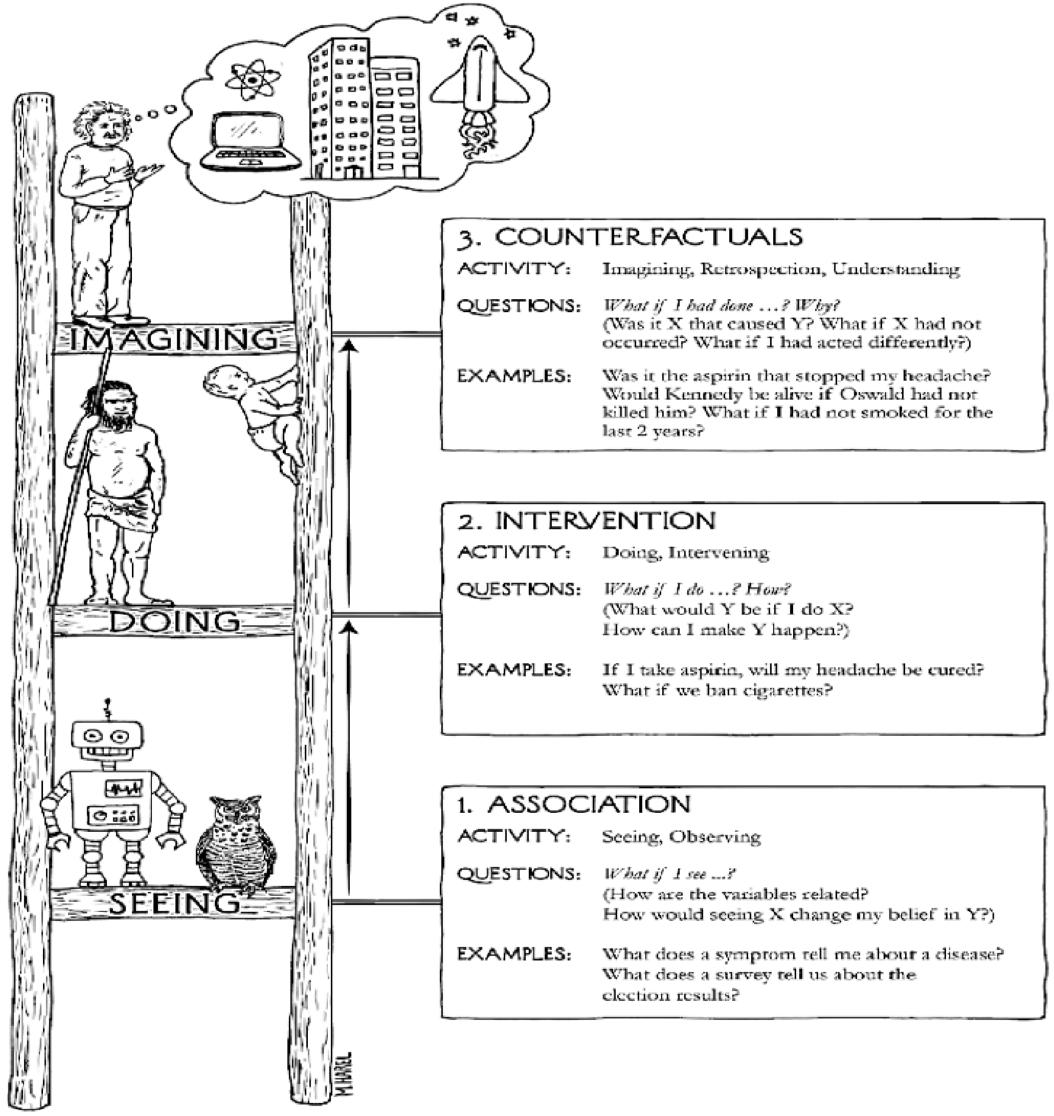


(a) Kuramoto (b) Boids (c) SIS metapopulation



Ladder of Causality

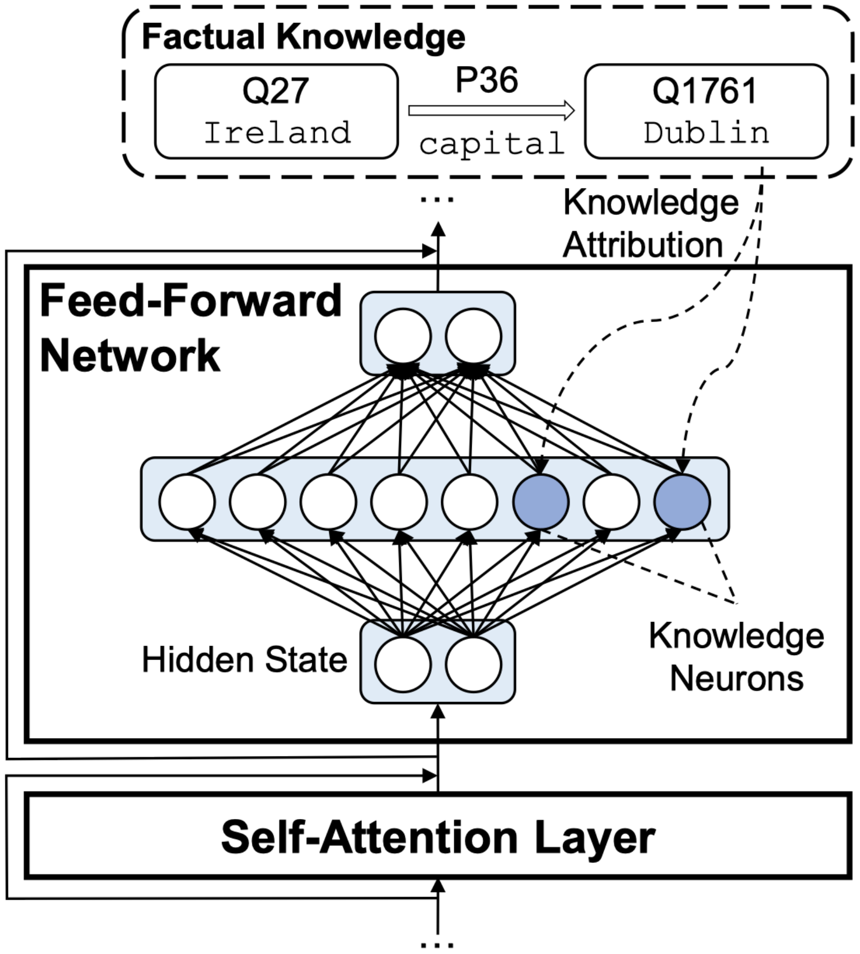


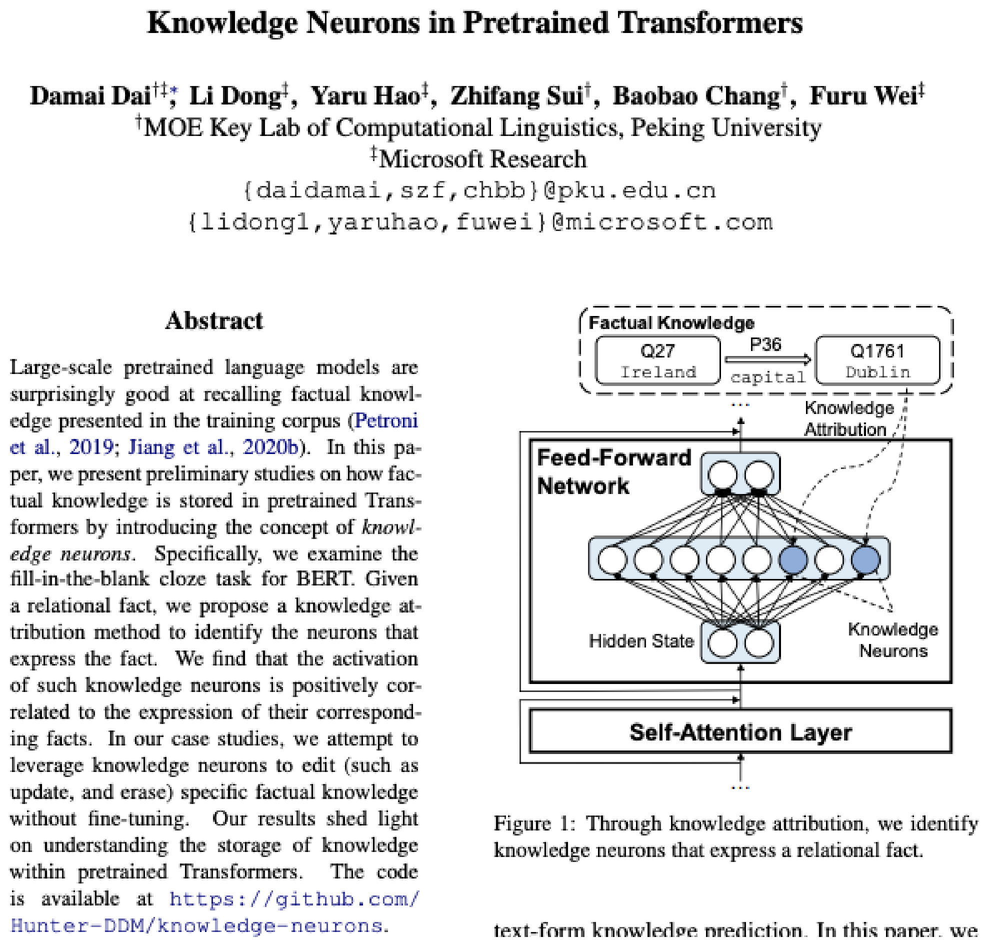


Summary

- Learning Complex Dynamics
- Learning Dynamics on Networks
- Learning Interaction Networks (Unsupervised)
- Learning Multi-scale Dynamics
- Applications of Surrogate Model

Retrieving knowledge from large models





Knowledge Neurons in Pretrained Transformers

Damai Dai[†‡]*, Li Dong[‡], Yaru Hao[‡], Zhifang Sui[†], Baobao Chang[†], Furu Wei[‡]
[†]MOE Key Lab of Computational Linguistics, Peking University
[‡]Microsoft Research
{daidamai,szf,chbb}@pku.edu.cn
{lidong1,yaruhao,fuwei}@microsoft.com

Abstract

Large-scale pretrained language models are surprisingly good at recalling factual knowledge presented in the training corpus (Petroni et al., 2019; Jiang et al., 2020b). In this paper, we present preliminary studies on how factual knowledge is stored in pretrained Transformers by introducing the concept of *knowledge neurons*. Specifically, we examine the fill-in-the-blank cloze task for BERT. Given a relational fact, we propose a knowledge attribution method to identify the neurons that express the fact. We find that the activation of such knowledge neurons is positively correlated to the expression of their corresponding facts. In our case studies, we attempt to leverage knowledge neurons to edit (such as update, and erase) specific factual knowledge without fine-tuning. Our results shed light on understanding the storage of knowledge within pretrained Transformers. The code is available at https://github.com/Hunter-DDM/knowledge-neurons.

Figure 1: Through knowledge attribution, we identify knowledge neurons that express a relational fact.

text-form knowledge prediction. In this paper, we

https://arxiv.org/pdf/2104.08696.pdf

Neural network attributions

Neural Network Attributions: A Causal Perspective

Aditya Chattopadhyay [1] Piyushi Manupriya [2] Anirban Sarkar [2] Vineeth N Balasubramanian [2]

Abstract

We propose a new attribution method for neural networks developed using first principles of causality (to the best of our knowledge, the first such). The neural network architecture is viewed as a Structural Causal Model, and a methodology to compute the causal effect of each feature on the output is presented. With reasonable assumptions on the causal structure of the input data, we propose algorithms to efficiently compute the causal effects, as well as scale the approach to data with large dimensionality. We also show how this method can be used for recurrent neural networks. We report experimental results on both simulated and real datasets showcasing the promise and usefulness of the proposed algorithm.

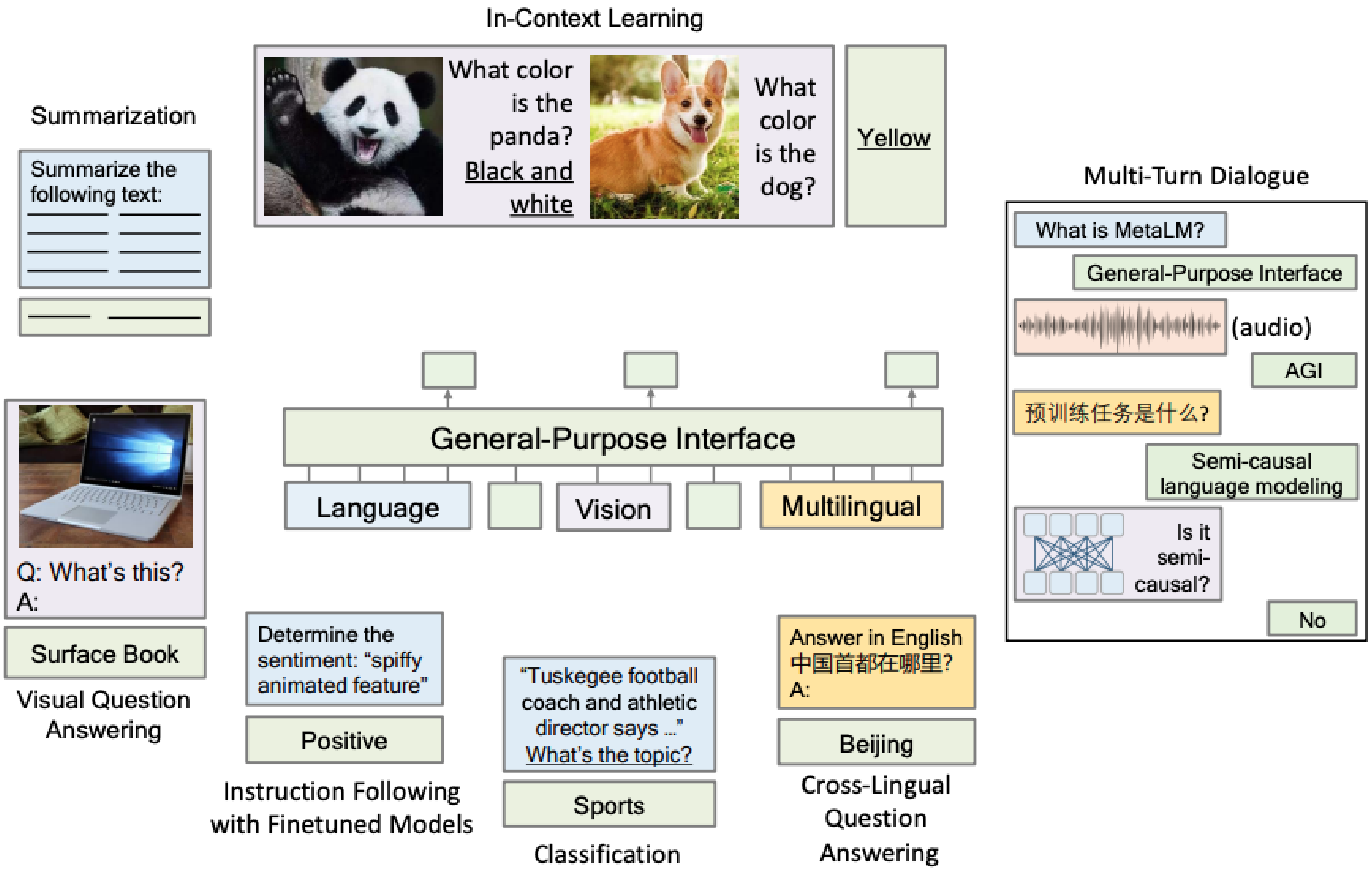
1. Introduction

way for a new paradigm, "explainable machine learning".

While the field is nascent, several broad approaches have emerged (Simonyan et al., 2013; Yosinski et al., 2015; Frosst & Hinton, 2017; Letham et al., 2015), each having its own perspective to explainable machine learning. In this work, we focus on a class of interpretability algorithms called "attribution-based methods". Formally, attributions are defined as the effect of an input feature on the prediction function's output (Sundararajan et al., 2017). This is an inherently causal question, which motivates this work. Current approaches involve backpropagating the signals to input to decipher input-output relations (Sundararajan et al., 2017; Selvaraju et al., 2016; Bach et al., 2015; Ribeiro et al., 2016) or approximating the local decision boundary (around the input data point in question) via "interpretable" regressors like linear classifiers (Ribeiro et al., 2016; Selvaraju et al., 2016; Zhou & Troyanskaya, 2015; Alvarez-Melis & Jaakkola, 2017) or decision trees.

https://arxiv.org/pdf/1902.02302.pdf

General Large models



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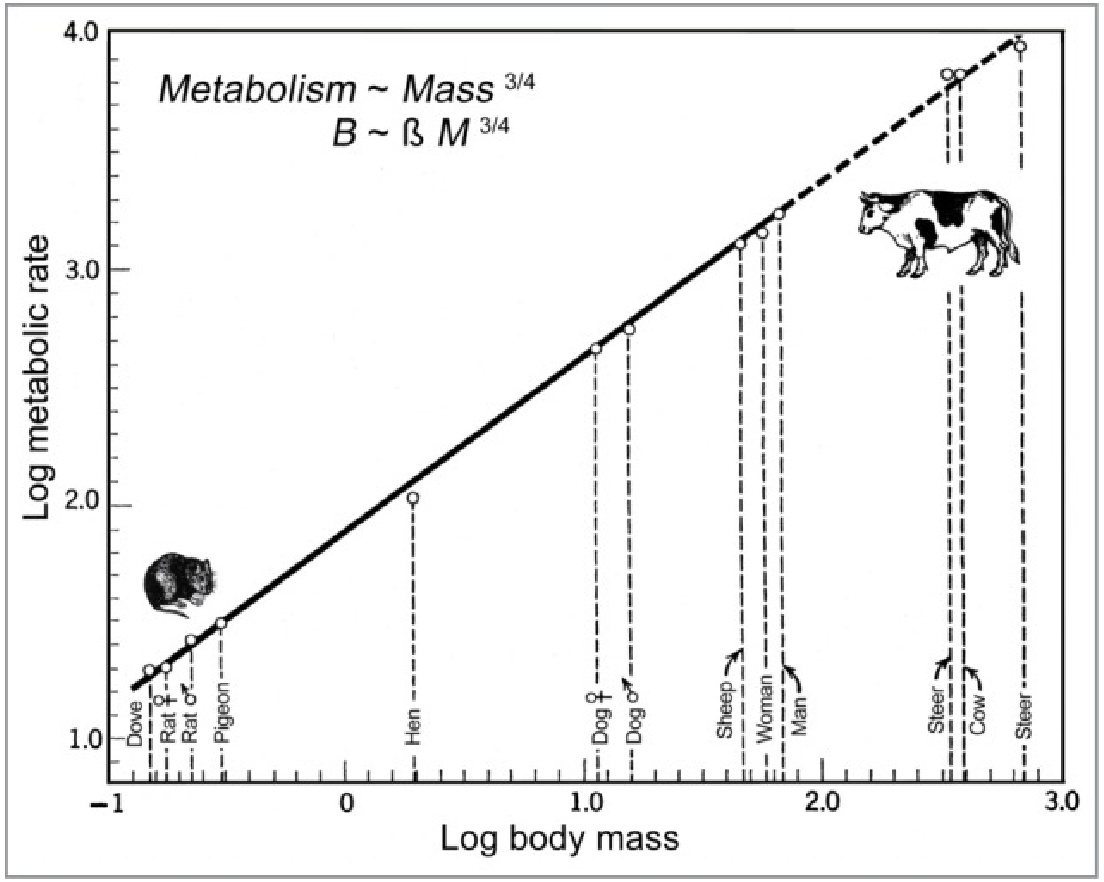
Outline

- AI for complex systems
- Complexity science for AI

Scaling laws



Scaling Laws in LLM

Scaling Laws for Neural Language Models

Jared Kaplan *
Johns Hopkins University, OpenAI
jaredk@jhu.edu

Sam McCandlish*
OpenAI
sam@openai.com

Tom Henighan
OpenAI
henighan@openai.com

Tom B. Brown
OpenAI
tom@openai.com

Benjamin Chess
OpenAI
bchess@openai.com

Rewon Child
OpenAI
rewon@openai.com

Scott Gray
OpenAI
scott@openai.com

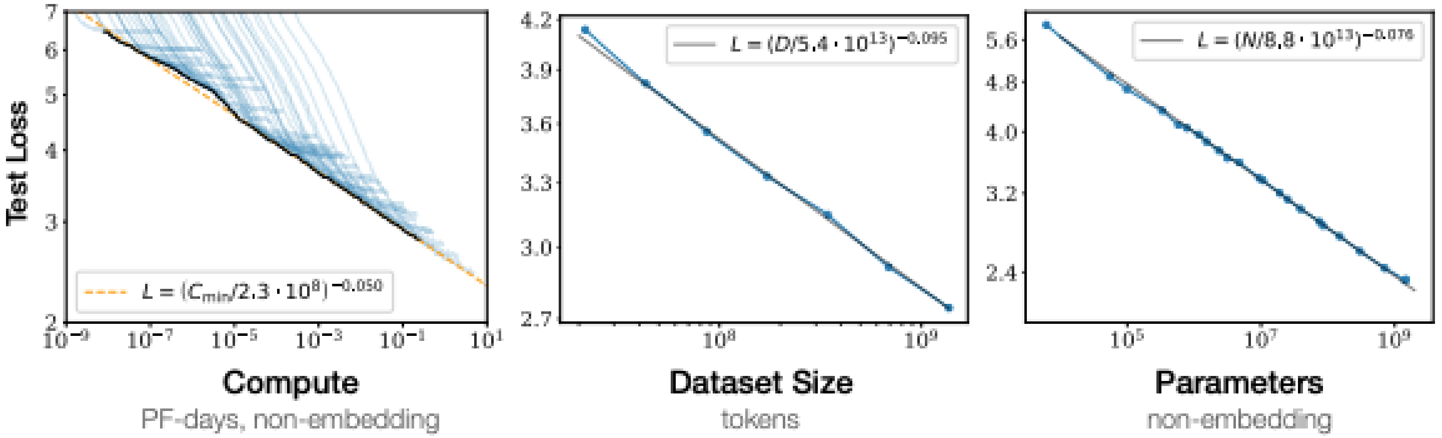
Alec Radford
OpenAI
alec@openai.com

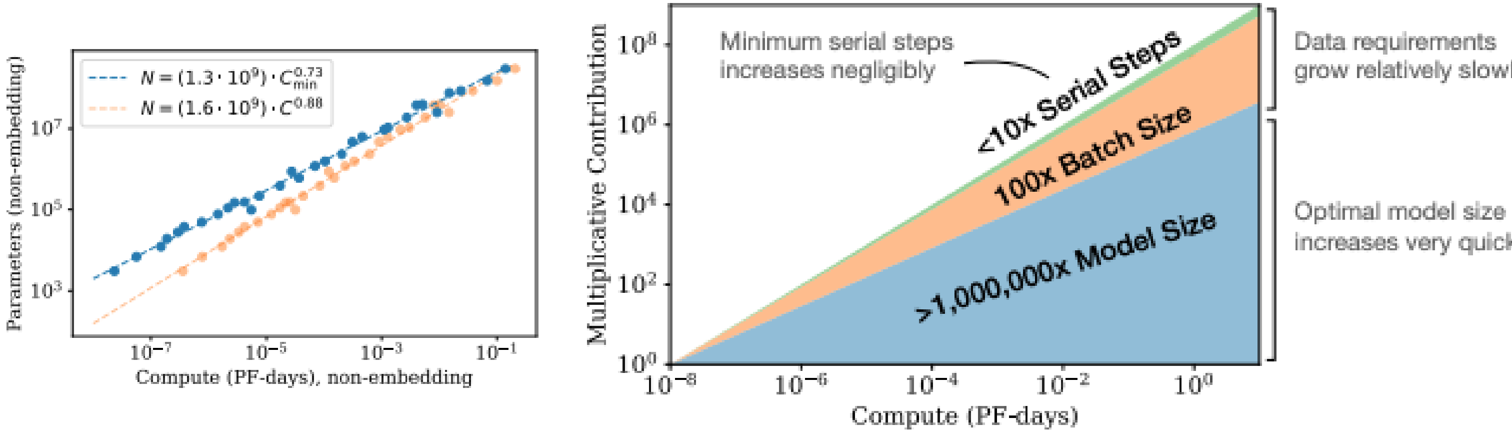
Jeffrey Wu
OpenAI
jeffwu@openai.com

Dario Amodei
OpenAI
damodei@openai.com

Abstract

We study empirical scaling laws for language model performance on the cross-entropy loss. The loss scales as a power-law with model size, dataset size, and the amount of compute used for training, with some trends spanning more than seven orders of magnitude. Other architectural details such as network width or depth have minimal effects within a wide range. Simple equations govern the dependence of overfitting on model/dataset size and the dependence of training speed on model size. These relationships allow us to determine the optimal allocation of a fixed compute budget. Larger models are significantly more sample-efficient, such that optimally compute-efficient training involves training very large models on a relatively modest amount of data and stopping significantly before convergence.





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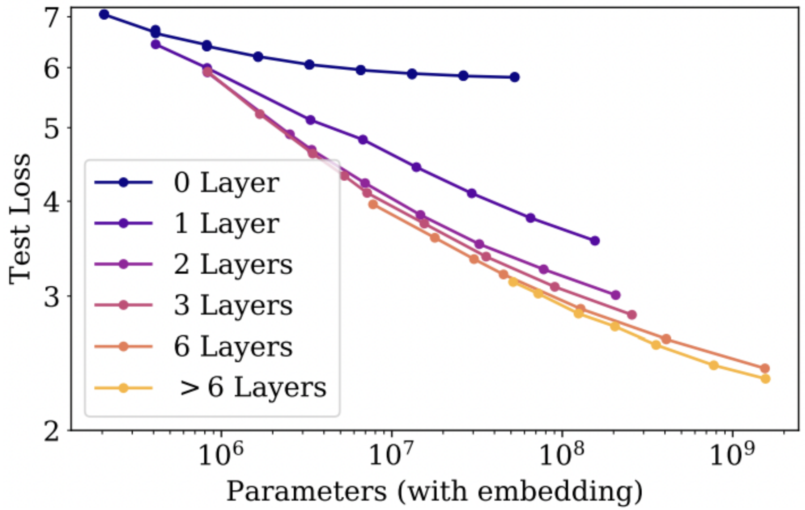
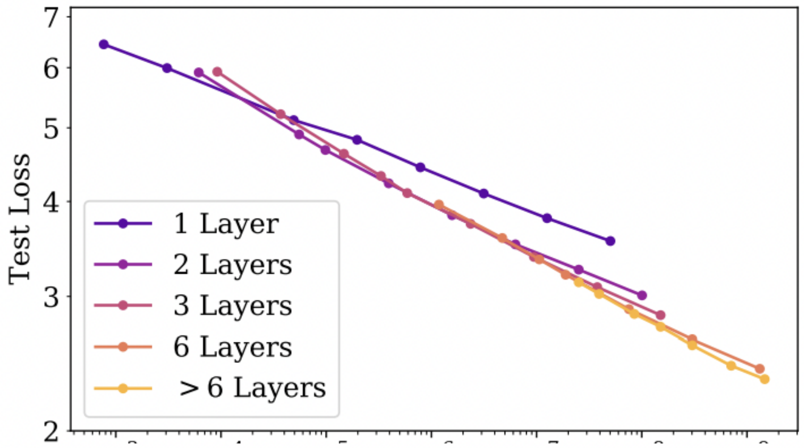
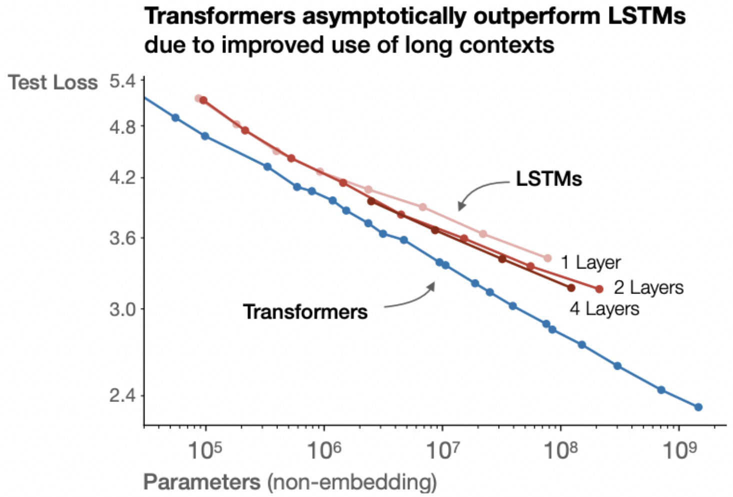
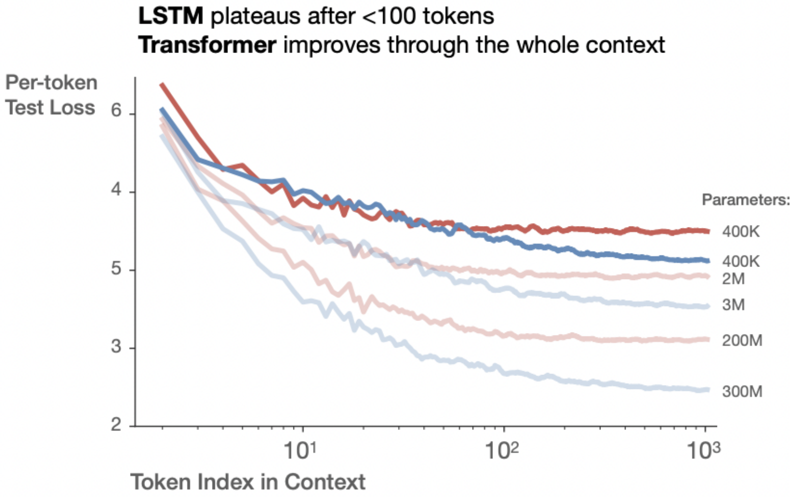
Independent with structures









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