Data-driven and Brain-inspired Autonomous Systems

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Engineering autonomous systems



(credit Weinstein, Kimbrell, Bohg, Frontiers Neurorobotics, Yellina)

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Engineering autonomous systems

- operate in unstructured, unknown, dynamic, contested environments
- learn from data and experience
- collaborate with systems and humans
- fail gracefully against tampering



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- learn from data and experience
- collaborate with systems and humans
- fail gracefully against tampering
- precision agriculture, transportation, search and monitoring, healthcare

My contributions towards autonomy





Distributed coordination and cooperation algorithms for teams of robots:

- persistent surveillance, search
- algorithm design, analysis, testing
- autonomous exploration, detection

My contributions towards autonomy





Expose and remedy vulnerabilities of (networked) cyber-physical systems:

- attack analysis, detection, design
- model-based and data-driven settings
- power networks, multi-agent systems





Model-based LQG control



x(t+1) = Ax(t) + Bu(t) + w(t)y(t) = Cx(t) + v(t)









- input (U), state (X), output (Y) data
- multiple noisy, open-loop trajectories
- (linear) unknown dynamics and noise



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- data overcomes lack of model/noise knowledge





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- \bullet direct vs indirect \Rightarrow variance vs bias tradeoff







- LQR + KF leads to data-driven LQG formulas
- data overcomes lack of model/noise knowledge
- direct vs indirect \Rightarrow variance vs bias tradeoff

Direct: no asymptotic bias, large variance Indirect: asymptotic bias, small variance Two distinct data regimes!

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Sensitivity to data perturbations and uncertainties

• data-driven and ML algorithms perform well in nominal conditions

Sensitivity to data perturbations and uncertainties

- data-driven and ML algorithms perform well in nominal conditions
- yet, brittle performance against perturbations and non-ideal conditions
- lack of robustness guarantees limits deployment in physical environments





Sensitivity to data perturbations and uncertainties

Insufficient data:

data driven and ML algorithms perform well in nominal conditions





- actual data not in training dataset
- different operating conditions (weather, lighting)
- increasing training data mitigates this problem





Sensitivity to data perturbations and Lipschitz constant	Safety certificates for open-loop data-driven algorithms
 Literature on regulating Lipschitz constant (very incomplete and a bit outdated): Lipschitz constant <i>after</i> training [Weng et al., 2018][Fazlyab et al., 2019] (computationally intensive, loose bounds, not useful for algorithm design) Lipschitz-regularized training [Gouk et al., 2018][Finlay et al., 2018] (no guarantees on neither nominal nor adversarial performance, not interpretable) distributionally robust training [Wong et al., 2018][Pauli et al., 2020] (not interpretable, no prescribed design of robustness, lack of adversarial guarantees) 	$ \begin{array}{c c} \min_{f \in \text{Lip}} \mathcal{L}(f) \\ \text{subject to } \lim(f) \leq \alpha \end{array} $
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Reverse engineer the human brain to advance AI





Wisconsin card sorting task

- each card has 3 attributes (number, shape, color)
- each attribute has 4 values (blue, green, yellow, orange)
- task: classify cards based on value of one attribute
- reward: after each classification player knows if correct

Reverse engineer the human brain to advance AI





Wisconsin card sorting task

Reverse engineer the human brain to advance AI





sort card based on attribute/value

Wisconsin card sorting task



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Reverse engineer the human brain for sustainable AI







brain \sim 10 W

laptop \sim 60 W

AI data center ~ 100 MW

- training GPT-3 same energy as driving to the moon and back
- GPT query consumes 15x more energy than Google query
- increasingly more models, larger models, more sophisticated GPUs, more users ...

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Reverse engineer the human brain for improved health

- personalized diagnostics therapies
- novel brain computer interfaces and implantable devices
- enhancement of brain functions and reversal of cognitive decline





[Medtronic] 15/25

Functional patterns of brain activity



Functional patterns of brain activity



- synchrony between brain regions long known (EEG, fMRI, [Berger & Gray, 1929])
- rich repertoire of synchrony patters (transient, long-range, clustered)
- different patterns are biomarkers of health and disease (epilepsy, Parkinson's)

Modeling functional patterns



- nodes = brain regions; edges = bundles of white matter fibers
- static brain networks carry structural and statistical information
- dynamic brain networks are useful for the prediction & control of neural dynamics

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Resting-state activity modeled by phase oscillators



each node of the brain network captures the dynamics of a population of neurons



Resting-state activity modeled by phase oscillators





Dynamical brain network to simulate neural activity

dynamical brain network with:

nodes = brain regions

edges = white matter fibers

node dynamics = Kuramoto



Analysis of functional patterns

Analysis of functional patterns

#1

#1

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[Menara et al., 2020 TCNS]



brain regions

correlated brain regions as synchronized oscillators







Cluster synchronization is possible if and only if:

• the network weights are *balanced*

• equal frequencies for all oscillators in the same cluster



Controllability of the human brain (using fMRI data):

- the brain is *structurally* controllable
- brain *hubs* are optimal *average* control states
- sparse brain are optimal for *modal* control states

[Menara et al., 2019 TAC] [Menara et al., 2019 Neuroimage] [Gu et al., 2015 Nature Comm.]



Control of functional patterns



[Menara et al., 2020 Roberto Tempo Award] [Menara et al., 2022 Nature Comm.]

- control knobs = network weights + oscillator frequencies
- biological constraints \Rightarrow positive weights, sparsity of interventions, magnitude



#2

Summary

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- data-driven LQG control
- sample complexity and asymptotic performance
- performance vs robustness tradeoffs for control/learning
 - brain-inspired decision making
 - network control for brain analysis (anatomy & function)
 - control-inspired methods for functional connectivity

Summary

My group















Collaborators











