Research Statement

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My work aims to develop foundational theory and computational tools, rooted in **machine learning, optimization, and control** for the design of **large-scale data-driven cyber-physical systems** (DDCPS) such as the smart-grid, software-defined networks and smart transportation systems. For such a theory to be successful, it must provide the non-asymptotic guarantees of contemporary high-dimensional statistics, the stability, safety and performance guarantees of robust control theory, and the ability to learn and adapt of data-driven systems, all while being applicable to safety-critical systems that are highly dynamic and interconnected, difficult to model, ever changing and of huge scale. The goal of my research is to develop such a theoretical framework and the corresponding computational tools needed to make these insights actionable. Ultimately, I aim to provide the first scalable, holistic and principled approach to the **design of large scale data-driven CPS control systems**.

My research program is centered around our recently developed framework for controller synthesis, which we call the System Level Approach (SLA) [1, 2, 3, 4]. By generalizing foundational concepts from classical and distributed optimal control, the SLA has already had significant impact in the controls community, and proved to be an essential technical tool in **combining machine learning with robust/optimal control** (see our recent paper [5]). Highlights of my research include:

- **Combining ML and control:** Our paper [5] describes a contemporary view that merges techniques from statistical learning theory and robust/optimal control to derive baselines for a "Learning LQR" optimal control problem wherein the system model to be controlled is unknown. Leveraging the SLA, we provide baselines delineating the possible control performance achievable given a fixed amount of data collected about the system, bringing rigor to reinforcement learning methods in continuous control.

- **A System Level Approach:**. The SLA to controller synthesis provides a novel convex parameterization of stabilizing controllers. This parameterization was key in deriving the end-to-end sample complexity bounds found in [5], and has also allowed us to synthesize optimal controllers for systems with hundreds of thousands of states using only a single laptop computer. This line of work has already generated 13 publications since 2014, including the **ACC 2017 Best Student Paper [3] award winner** and a tutorial paper [4] (and session) at the upcoming CDC 2017. I have further been invited to give 11 seminars on this work in 2017, at venues such as USC, UCSB, UC Berkeley, MIT, Stanford, McGill, Harvard, U. of Washington and the U. of Adelaide.

- **Control architecture co-design:** A major challenge in designing large-scale control systems is determining how to optimally allocate architectural resources, i.e., where to place actuators, sensors and the communication channels interconnecting them. To address this problem, we developed the Regularization for Design (RFD) framework, which provides a computational framework with theoretical guarantees for the co-design of an optimal controller and the actuation/sensing/communication architecture needed to implement it. The importance of this work was recognized by the controls community, with [6] winning the **CDC 2013 Best Student Paper Prize**.

- **Application areas:** We are currently applying the SLA to study tradeoffs in achievable performance in primary frequency control of power grids [7] (with Steven Low at Caltech), and in congestion management in software defined networks [8] (with the Huawei Future Network Theory Lab). I have also been involved with projects related to synthesizing treatment strategies for HIV and Cancer [9], and reverse engineeringing of the human sensorimotor control system [10].

Going forward, I envision a synergistic research program wherein the needs of large-scale DDCPS inform the development of new methods in online learning and control. A major focus will be to combine the safety and robustness guarantees of model predictive and robust control with the flexibility of reinforcement learning based methods, combined with the validation of these methods in software defined networks, power systems and other CPS, such as robotics and automated driving systems.

1 End-to-End Sample Complexity Guarantees for Optimal Control

Given the dramatic successes in machine learning and reinforcement learning (RL) over the past half decade, there has been a resurgence of interest in applying these techniques to continuous control problems in robotics, self-driving cars, and unmanned aerial vehicles. Though such applications appear to be straightforward generalizations of standard RL, few fundamental baselines have been established prescribing how well one must know a system in order to control it. In [5], we describe a contemporary view that merges techniques from statistical learning theory and robust control to derive baselines for a "Learning LQR" optimal control problem wherein the system model to be controlled is unknown. We propose a simple 3-step strategy: (i) use least-squares to estimate a model based on experiments, (ii) use bootstrapping techniques to build probabilistic guarantees about the distance between the estimated and true model, and (iii) solve an optimal control problem that robustly optimizes the performance of the system while guaranteeing stable and robust execution for any realization of the estimated model uncertainty. We provide characterizations of the complexity of learning a linear-time-invariant systems and identify tradeoffs based on how easily controlled a system is, and further provide sub-optimality guarantees for the robustly stabilizing controller synthesized using the aforementioned procedure. These results represent a modern take on robust, adaptive and RL based control, and to the best of our knowledge, establish the first end-to-end baselines for learning in an LQR problem that do not require restrictive or unrealistic assumptions. This is of course just a first step towards the broader goal of bringing rigor to RL based control, with the end-goal being to guarantee the safe, efficient and robust execution of learning systems as applied to continuous control problems: I outline these future plans in §4.

A key enabling technical tool in deriving these results is the System Level Approach to Controller Synthesis [1, 2, 3, 4], which for the first time allows for clean and interpretable bounds on the performance of a robust controller to be obtained in terms of the size of the uncertainties of the system estimates. As we describe next, the SLA also represents a major breakthrough in the scalability of distributed optimal control methods.

2 A System Level Approach to Controller Synthesis

As modern CPS become increasingly dynamic and decentralized, feedback control systems will be essential in guaranteeing their reliable and robust behavior – indeed robust and predictable behavior at the component level of a system allows higher system-level tasks, such as resource allocation, learning and exploration, and optimizing social/economic welfare, to be made simpler and more efficient. However, even seemingly simple decentralized optimal control problems are intractable (e.g., Witsenhausen's counterexample), making it a challenge to extend foundational results of the field (e.g., the Youla parameterization and DGKF state-space solutions) to the distributed setting. A recent breakthrough was the identification of a broad class of tractable (convex) distributed optimal control problems by Rotkowitz and Lall in 2006. These systems satisfy a quadratic invariance (QI) property, and allow classical (Youla) based synthesis methods to be used to compute structured controllers. Although QI was an important step forward, the resulting controllers were not scalable to synthesize or implement. This lack of scalability has prevented the adoption of these methods in practice, limiting their scope to systems with at most a few hundred states.

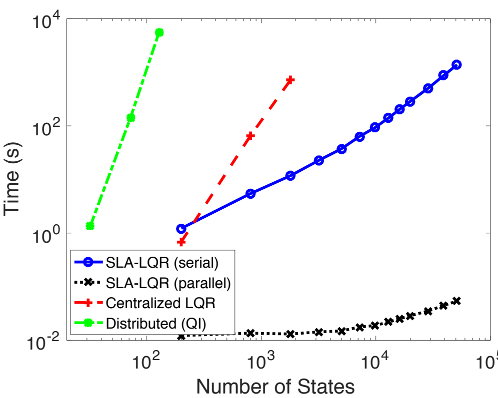

Figure 1: Computational time needed for the synthesis of centralized, distributed (QI) and localized (SLA) LQR controllers as a function of system size.

We address this issue by developing the System Level Approach to Controller Synthesis [1, 2, 3, 4], in which we present an alternative to the Youla parameterization that is naturally suited to distributed (structured) controller synthesis. By rethinking and generalizing this foundational pillar of modern control theory, we are able to identify the broadest known class of convex constrained linear optimal control problems, of which QI distributed optimal control problems are a special instance.[1] Unlike its predecessors, our approach allows for the synthesis localized system responses and corresponding controllers, in which local control policies depend only on local subsets of the global system model and state (cf. [2, 4, 11, 12] and references therein). The importance of this contribution was recognized by the controls community, with the paper [3] being awarded the **Best Student Paper Award at the 2017 IEEE American Control Conference**.

The notion of locality, which could not be captured by existing theory, allows us to scale structured optimal controller synthesis methods to systems of arbitrary size (assuming sufficient parallel computing power): an example illustrating the benefits of our approach on controller synthesis computation time are shown in Figure 1. In addition to the aforementioned locality constraints, the system designer can simultaneously impose multiple performance objectives, structural constraints on the controller, robustness to quantization in the communication and internal computation of the controller, robustness to modeling error, and as described in the next section, limits on the actuation, sensing and communication complexity of the resulting controller. Thus, by generalizing the foundational results of QI and the Youla parameterization, the System Level Approach provides, for the first time, a unified framework for customized controller synthesis that is applicable to large-scale distributed systems. We invite the reader to visit our tutorial website[2] `http://www.cds.caltech.edu/syslevelsyn` which we developed as a compliment to our CDC 2017 Tutorial session: this site will serve as a resource to the controls community who wish to use the SLA by providing tutorial videos, collecting relevant technical papers, providing demo-code and posing open research problems.

3 Regularization for Design of Control Architectures

A system's ability to provide robustness and/or performance is directly determined by its actuation, sensing and communication architecture: the more of these resources are present, the better we expect the performance of an optimal controller to be. However such architectural components can be expensive to build, install and maintain, and thus from an economic or energetic perspective there is a real motivation to use as few actuators, sensors and communication links as possible. The result is a tradeoff between architectural complexity and closed loop performance that, naively explored, would require enumerating a combinatorial design space. In order to explore this design space in a computationally tractable manner, we developed the **Regularization for Design** (RFD) framework [13, 6] which provides a control system designer with tractable algorithmic tools (based on convex optimization and atomic norm regularization) for the co-design of a distributed optimal controller and the actuation, sensing and communication architecture used to implement it. This work was the first to provide a computational framework for the simultaneous design of actuation, sensing and communication architectures for dynamic output-feedback controllers, unifying and generalizing existing results in controller architecture design. We were also the first to observe that designing a controller architecture can be cast as finding structured solutions to a particular linear inverse problem, allowing us to draw on the rich theory developed in the structured inference literature to provide conditions under which optimally structured controllers are identified using finite dimensional convex optimization.

A surprising outcome of this line of work is the identification of systems for which near centralized performance can be obtained using sparse controller architectures, thus suggesting that judiciously placed architectural resources can have a significant impact on closed loop performance. The importance of this work was recognized by the control community, which awarded the **sole-author** paper [6] the **Best Student Paper Prize of the 2013 IEEE Conference on Decision and Control**. Finally, although this line of work was initially developed under the Youla/QI framework, we have since integrated RFD into the SLA (cf., [1, 2, 11]), thus allowing controller architectures to be designed for large-scale systems.

By integrating the architecture co-design capabilities of RFD with the generality and scalability of the SLA to controller synthesis, it appears that we now have, for the first time, a scalable, holistic and principled approach to the **design of large-scale CPS control systems**. As a proof of concept, we have applied these tools to a 200-state model of linearized swing dynamics (synthetic topology and and parameter values)

[1]Both the papers on the Youla parameterization and QI were awarded the Axelby award for the best paper published in the IEEE Transactions on Automatic Control.

[2]This website will be live by December 2017, and will be continuously updated over the upcoming months.

in [2], and are currently applying them to larger and more realistic power system models based on IEEE test cases [7]. Our aim in this latter work is to provide a systematic study of the fundamental limits imposed on system performance by communication delay, actuation and sensing density, and degree of coordination in the context of large-scale power systems: this is now possible thanks to our novel framework because we can now, for the first time, compute and quantify the performance of distributed optimal controllers at scale.

4 Future Plans

Large-Scale Data-Driven Cyber-Physical Systems Above I have described two key components towards the development of a theory of large-scale DDCPS, namely an integration of statistical learning theory with robust control and the SLA to controller synthesis. Whereas the former results considered the simplest of settings: a centralized state-feedback LQR problem, the latter are applicable to large-scale problems. Future work will look to combine these two frameworks together, exploiting structure and sparsity to gain computational and complexity advantages throughout, with the aim of developing a truly modern theory of learning and control that is applicable to large-scale systems.

Specific research goals in the context of learning and control include extending our existing results: (i) to include online learning and control (and to develop corresponding regret bounds), (ii) to handle more complicated system dynamics and objectives, leading to more sophisticated and realistic tradeoffs between exploration and exploitation (this is not an issue for LTI systems as the model can be identified anywhere), and (iii) to guarantee safety (with respect to state and input constraints) throughout the learning procedure.

Control specific research goals include: (i) developing a theory of robustness, akin to that from the 90s centered around H_∞ optimal control and μ-synthesis, that is applicable to large-scale distributed systems. Such classical methods are standard in industries such as aerospace and process control, and by extending them to large-scale distributed settings, are poised to have significant impact on emerging areas such as smart-grids and intelligent transportation systems; (ii) integrating these ideas into a model predictive control (MPC) like framework, allowing them to be applied to nonlinear systems and systems with state and input constraints. MPC is another industry standard that has failed to gain widespread use in large-scale settings, something that I aim to change; and (iii) exploiting the strong priors endowed on system response structure by locality to develop novel and efficient fault detection and learning algorithms for the local redesign of DDCPS under failure and modeling error conditions.

Application to software defined networking A defining feature of SDN is the abstraction introduced between the traditional forwarding (data) plane and the control plane. This abstraction allows for an explicit separation between data forwarding and data control, and provides an interface through which network applications can programmatically control the network. This in turn allows for diverse, distributed application software to be run using diverse, distributed hardware in a seamless way. This added flexibility leads to new architectural and algorithmic design challenges, such as deciding which aspects of network functionality should be implemented in a centralized fashion in the application plane, which components of network structure should be virtualized by the control plane, and which elements of network control should remain in the data plane. With this increased design freedom comes the opportunity to develop a rich theory of network architecture that informs the design of more sophisticated, dynamic and reactive network control algorithms. To do so, we take inspiration from the Layering as Optimization Decomposition framework, which can be viewed as the first theoretical framework for network architectures that was able to both reverse engineer existing network protocols, as well as inform the design and forward engineering of novel protocols that outperformed the current state of the art. Our aim is now to extend this approach to an environment in which dynamic, local and fast time-scale control can be integrated with global, slower-time scale control.

My approach to advancing this research agenda is centered around three components: (1) the introduction of novel "reflex" layers to network control, wherein fast-time scale (e.g., order round trip time) fluctuations are explicitly addressed; (2) the integration of these novel "reflex" layers with more traditional network control tasks, such as traffic engineering, by exploiting my novel approach to layering [14]; and (3) collaborations with domain experts for the implementation and evaluation of practical algorithms at scale.

As a concrete example of progress made in this respect, I have developed and implemented (in collaboration with Ao (Kevin) Tang and his group at **Cornell University**) a novel approach to in-network congestion management, which we call High Frequency Traffic Control (HFTraC) [8], that operates at the network layer at the timescale of round-trip time. HFTraC's objective is to minimize a weighted sum of queue length and flow rate fluctuation by utilizing available buffer space in routers network-wide, allowing for the principled exploration and optimization of the tradeoff between packet loss % and queueing length. Another key component of this work is quantifying how the achievable performance of HFTraC is determined by the network architecture used to implement it (e.g., whether router service rate decisions are computed in a decentralized, distributed or centralized manner). Finally, in order to validate the effectiveness of HFTraC, we implement and evaluate its performance on a custom designed experimental testbed, a Mininet emulator, and a production wide area network (WAN). Building on this success, I am currently exploring the integration of HFTraC with more traditional network tasks, such as traffic engineering (TE), as well as working with the **Huawei Future Network Theory Lab** to deploy these ideas at scale. This work has shown enough promise to secure renewed funding from the Huawei Future Network Theory Lab for John C. Doyle.

Interdisciplinary research Key to developing a truly interdisciplinary research program is establishing collaborations with domain experts. I have already done so in the areas of SDN (collaboration with Huawei, invited speaker at the 2016 NSF AiTF Workshop on Algorithms and SDN, keynote speaker at the 2017 ACEMS Workshop on Challenges of Data and Control of Networks), power systems (invited participant at the 2017 NREL workshop on Autonomous Energy Grids) and neuroscience (invited speaker at the 2017 Living Machines workshop on Control Architectures). I plan to continue to promote this synergy between application and theory by rigorously addressing the needs of domain experts across a breadth of CPS areas.

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