Technical Report 128

Project Title:

Large-Scale Linear Programs in Planning and Prediction

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WNCG

June 2017

Data-Supported Transportation Operations & Planning Center (D-STOP)

A Tier 1 USDOT University Transportation Center at The University of Texas at Austin

CENTER FOR TRANSPORTATION RESEARCH

Wireless Networking & Communications Group

D-STOP is a collaborative initiative by researchers at the Center for Transportation Research and the Wireless Networking and Communications Group at The University of Texas at Austin.

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
D-STOP/2017/128		

4. Title and Subtitle	5. Report Date
Executive Summary: Large-Scale Linear Programs in Planning and Prediction	June 2017
	6. Performing Organization Code

7. Author(s)	8. Performing Organization Report No.
Constantine Caramanis	Report 128

9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
Data-Supported Transportation Operations & Planning Center (D-STOP) The University of Texas at Austin 1616 Guadalupe Street, Suite 4.202 Austin, Texas 78701	11. Contract or Grant No. DTRT13-G-UTC58

12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
Data-Supported Transportation Operations & Planning Center (D-STOP) The University of Texas at Austin 1616 Guadalupe Street, Suite 4.202 Austin, Texas 78701	14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the U.S. Department of Transportation, University Transportation Centers Program.

16. Abstract

Large-scale linear programs are at the core of many traffic-related optimization problems in both planning and prediction. Moreover, many of these involve significant uncertainty, and hence are modeled using either chance constraints, or robust optimization. Chance constraints and robust optimization are by now classical approaches for dealing with uncertainty. The ultimate goal in each of these areas, is to find an explicit convex reformulation that provides some approximation to the original (uncertain) optimization problem. The work in these areas has helped us obtain a nearly comprehensive understanding of when convex reformulations (and approximations) are possible, and what the quality of the approximation is. Yet little has been said about truly tractable solutions—solutions where running time for the uncertain problem is comparable (perhaps even less than!) the time to solve the problem without any uncertainty. As networks grow in size, and our ability to capture more data rapidly increases, it is of paramount importance to rethink our theory of robust and uncertain optimization for transportation applications, to one that is computationally oriented..

17. Key Words	18. Distribution Statement
	No restrictions. This document is available to the public through NTIS (http://www.ntis.gov): National Technical Information Service 5285 Port Royal Road Springfield, Virginia 22161

19. Security Classif.(of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified		

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

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Acknowledgements

The authors recognize that support for this research was provided by a grant from the U.S. Department of Transportation, University Transportation Centers.

Executive Summary: Large-Scale Linear Programs in Planning and Prediction

Linear programs – including network flow problems – are so central to planning and prediction problems that they can be considered as *computational primitives*. That is, they are computational building blocks fundamental to the modeling process. A key reason for this is that traditionally, linear programming has been considered to be one of the most tractable classes of optimization problems, with efficient interior point methods, as well as highly stable variants of the simplex method, which have repeatedly been demonstrated to have excellent performance in practice. Nevertheless, the complexity of solving linear programs grows super-linearly in the problem size – faster than $O(n^3)$ for problems with n variables. While this has traditionally not presented significant bottlenecks, for problems where n grows, it promises to be a significant impediment to future research, and potentially limit our ability to model more complex systems.

This promises to be a significant challenge as we move to modeling highly connected systems. Autonomous vehicles, along with increased capability of V2V and V2I communication and connectivity, have the potential to produce transportation systems that have significant coupling and correlation across very large geographic distances. Particularly in more dense urban settings, the scale of models must necessarily grow accordingly.

In this line of research, we have sought to develop highly scalable algorithms for linear programming. Our inspiration is the tremendous advances in first order algorithms for convex optimization problems, that have seen remarkable success in large scale machine learning problems. One of the key insights in this domain is that the accuracy of the solution is not the bottleneck – rather, it is the size that presents problems. The most used algorithms for linear programming, including interior point methods and the simplex algorithm, have an excellent scaling with respect to the final accuracy or error of the solution. This makes these approaches most appropriate when the application mandates that the accuracy of the final solution be extremely accurate. Examples of such applications include, for example, channel decoding via linear programming. In contrast, large scale machine learning has adopted algorithms that scale very slowly in dimension, though may present a higher cost to achieve very low error solutions. We have investigated the impact of these algorithms, including Mirror Descent, and also modifications of more sophisticated and parallelizable algorithms based on the Multiplicative Weights Framework.

Note: A full report is forthcoming.