



香港中文大學統計學系

Department of Statistics

THE CHINESE UNIVERSITY OF HONG KONG

# SEMINAR

DEPARTMENT OF STATISTICS  
THE CHINESE UNIVERSITY OF HONG KONG

## An algorithmic view of $\ell_2$ regularization and some path following algorithms

### INVITED SPEAKERS

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### TIME

May 17, 2022 (Tuesday) · 9:00 am - 10:00 am

### ABSTRACT

In this talk, I will first introduce an interesting algorithmic view of  $\ell_2$ -regularization. This is discovered through establishing an equivalence between the  $\ell_2$ -regularized solution path and the solution of an ordinary differentiable equation (ODE). This equivalence reveals that the solution path can be viewed as the flow of a hybrid of gradient descent and Newton method applying to the empirical loss, which is similar to a widely used optimization technique called trust region method. This algorithmic view of  $\ell_2$  regularization is in contrast to the conventional belief that the  $\ell_2$  regularization solution path is similar to the gradient flow of the empirical loss. In the second half of the talk, I will focus on some new path-following algorithms motivated by the algorithmic view. These algorithms can efficiently approximate the  $\ell_2$ -regularized solution path and provide efficient ways to select optimal tuning parameter. In particular, I will introduce a novel algorithm for selecting the grid points and stopping criteria to guarantee a given level of desired suboptimality for the solution path. I will also provide computational complexity results for the Newton method and gradient descent method when used as the basis algorithm for the path following algorithms. In particular, it is shown that in order to achieve an  $\epsilon$ -suboptimality for the entire solution path, the number of Newton steps required for the Newton method is  $\mathcal{O}(\epsilon^{-1/2})$ , while the number of gradient steps required for the gradient descent method is  $\mathcal{O}(\epsilon^{-1} \ln(\epsilon^{-1}))$ . Finally, I will use  $\ell_2$ -regularized logistic regression as an illustrating example to demonstrate the effectiveness of the proposed algorithms.

### VENUE

Zoom ID: 606 898 8598 · Password: cuhkstat · [Zoom link](#)