

## Remarks

Michael is good at statistical learning

## Books that will help

<http://www.statsblogs.com/2014/12/30/machine-learning-books-suggested-by-michael-i-jordan-from-berkeley/>

## My Outline

**【7.22 p.m.】**

- theme

Artificial Intelligence: perspective and challenges

Inference & privacy

no slides

**【7.23】**

- theme

<a.m.> the cost function of some ML algorithms

logistic regression, LASSO regression, linear regression and show the differences of the choice of norm; PCA; K-Means.

<p.m.>

The convergence of convex optimization

Talking about Lipschitz, the bound and convergence rate of optimization algorithm, which turns out always with respect to  $t$  (the number of train data)

No slides

**【7.24】**

- theme

- show the necessity of smoother assumption and strong convex assumption;
- Bregman divergence; and derive the boundary of Bregman divergence. (平滑操作大于强凸)
- derive the convergence rate with assumption of smooth and strong convex
- P(projection)GD、SGD、Controlled SGD (SVRG, LiHua lei)、Mirror Descent (Nemirovsky)
- How to get rid of saddlepoints:  
one is first-order stationary points and make a choice;  
the other is PGD(Perturbed)
- Derive the correctness of the operational mirror algorithms

- Summary

- 1) It turns out the boundary and convergence rate always influenced by the number of train data

- 2) More train data always help us get a more optimum result, at least won't decrease
- 3) It also with respect to the Lipschitz condition
- 4) It seems the mirror descent is similar to the kernel function, right??

**【7.25】**

- theme
  - i. Derive the boundary of mirror descent
  - ii. See slides of 《Variational, Hamiltonian and Symplectic Perspectives on Acceleration》
  - iii. Change the O.S. (optimization system) as a problem of energy
  - iv. Some discussions of model free and model setting