



# Lecture 13. Review and Advanced Topics

Advanced Optimization (Fall 2025)

Peng Zhao

[zhaop@lamda.nju.edu.cn](mailto:zhaop@lamda.nju.edu.cn)

Nanjing University

# Part 1. Offline Optimization

- Lipschitz Optimization (Lec 3)
  - Gradient Descent: first/second gradient descent lemma
  - Polyak step size
- Smooth Optimization (Lec 4)
  - Gradient Descent (one-step improvement lemma)
  - Polyak momentum
  - Nesterov's acceleration method
  - Composite Optimization

**How: use gradient information to establish convergence**

# Part 2. Online Optimization

- From a fixed objective  $F(\mathbf{x})$  to an interactive objective  $f_t(\mathbf{x})$
- Problem-independent Regret (Lec 5 & 6 & 7)
  - Lec 4: Online Gradient Descent
  - Lec 5&6: Online Mirror Descent
    - for PEA & exp-concave; and for general geometry
  - Lec 4: (Weighted) Online-to-Batch Conversion
    - $1/\sqrt{T}$  for Lipschitz and convex;  $1/T$  for Lipschitz and strongly convex

**How: handle interaction and exploit geometry to optimize regret**

# Part 2. Online Optimization

- From a fixed objective  $F(\mathbf{x})$  to an interactive objective  $f_t(\mathbf{x})$
- Problem-dependent Regret (Lec 8 & 9)
  - Adaptive Online Learning: small-loss PEA, self-confident tuning
  - Lec 9: Optimistic OMD
    - general optimistic bound
    - small-loss, gradient-variance, gradient-variation
  - Lec 9: (Stabilized) Online-to-Batch Conversion
    - GV regret+O2B  $\rightarrow 1/T$ ; and GV regret+stabilized O2B  $\rightarrow 1/T^2$  for smooth functions

**How: leverage predictive info to achieve faster rate guarantees**

# Part 3. Bandit Optimization

- From gradient feedback to partial-information feedback
- Adversarial Bandits (Lec 10)
  - Multi-armed Bandits: importance-weighting (IW) loss estimator
  - Bandit Convex Optimization: gradient estimator based on perturbation
  - More advanced: anisotropy exploration based on self-concordant barrier
  - Exploration-exploitation in adversarial bandits

**How: use single function value to estimate the gradient**

# Part 3. Bandit Optimization

- From gradient feedback to partial-information feedback
- Stochastic Bandits (Lec 11 & Lec 12)
  - Multi-armed Bandits
    - ETC,  $\epsilon$ -greedy, Upper Confidence Bound, TS
  - Linear Bandits
    - least-square estimator, UCB based self-normalized concentration
  - Exploration-exploitation in stochastic bandits

**How: adaptive exploration based on the statistical estimation**

# Many yet to cover

- Variance Reduction (HW1 mentions a bit)
- Non-convex Optimization (HW1 mentions a bit)
- Adaptive Optimization like AdaGrad/Adam (HW2 mentions a bit)
- Online MDPs/Control/RL (HW2 mentions a bit)
- Online Games/Minmax Optimization
- Contextual Bandits...

# Four Talks

- Bandit Optimization
  - Yu-Jie Zhang, Sheng-An Xu, Peng Zhao, and Masashi Sugiyama. Generalized Linear Bandits: Almost Optimal Regret with One-Pass Update. *NeurIPS 2025*.
  - Jing Wang, Yu-Jie Zhang, Peng Zhao, and Zhi-Hua Zhou. Heavy-Tailed Linear Bandits: Huber Regression with One-Pass Update. *ICML 2025*.
- Online Optimization
  - Yu-Hu Yan, Peng Zhao, and Zhi-Hua Zhou. A Simple and Optimal Approach for Universal Online Learning with Gradient Variations. *NeurIPS 2024*.
  - Yuheng Zhao, Yu-Hu Yan, Kfir Yehuda Levy, Peng Zhao. Gradient-Variation Online Adaptivity for Accelerated Optimization with Hölder Smoothness. *NeurIPS 2025*.

# 腾讯匿名问卷反馈



**高级优化2025 课程反馈**  
诚邀您填写本问卷，扫码即可！