**EE 290 Mathematics of Data Science**

# Final Project

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## Project Logistics

The final project can either be a literature review or include original research.

1. **Literature review**. We will provide a list of related papers not covered in the lectures, and the literature review should involve in-depth summaries and exposition of one of these papers.
2. **Original research**. It can be either theoretic or experimental (ideally a mix of the two), with approval from the instructor. If you choose this option, you can do it either individually or in groups of two. You are encouraged to combine your current research with your final project.

There are 3 milestones / deliverables to help you through the process.

1. **Proposal (due Oct. 15).** Submit a short report (no more than 1 page) to the course staff mailing list stating the papers you plan to survey or the research problems that you plan to work on. Describe why they are important or interesting, and provide some appropriate references. If you elect to do original research, please do not propose an overly ambitious project that cannot be completed by the end of the semester, and do not be too lured by generality. Focus on the simplest scenarios that can capture the issues youd like to address.
2. **In-class presentation (Dec. 3 and Dec. 5).** Prepare an oral presentation with slides (the exact time will depend on the number of projects in the class). Focus on high-level ideas, and leave most technical details to your report.
3. **A written report (due Dec. 15).** You are expected to submit a final project reportup to 8 pages in NeurIPS format with unlimited appendix summarizing your findings / contributions. You must turn in an electronic copy to the class staff email or submit via gradescope.

The following are a few references collected under certain topics. You are free to dig up more references of relevance for the project you end up pursuing.

1. **Analysis of spectral method**

   References: (Huang et al., 2016; Gao et al., 2017; Abbe et al., 2017; Le et al., 2017; Huang et al., 2017)

2. **Average case lower bound**

   References: (Ma et al., 2015; Brennan et al., 2019; Brennan and Bresler, 2019b,a)

3. **Adaptive estimation**

   References: (Bickel, 1982; Birgé and Massart, 1997; Birgé et al., 2001; Yang, 2000; Leung and Barron, 2006; Abramovich et al., 2006; Su et al., 2016; Tsybakov, 2014; Ostrovskii et al., 2018)

4. **Uncertainty quantification**

   References: (Javanmard and Montanari, 2013, 2014; Guigues et al., 2017; Juditsky et al., 2019; Chen et al., 2019b)

5. **Convex optimization and non-convex optimization for statistical inference**

   References: (Chen et al., 2019a)

## References


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