EC 2016 Tutorial: 
Elicitation and Machine Learning* 

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Abstract / overview. The tutorial contains two parts. Part one covers the key concepts and tools from the theory of elicitation of predictions from self-minded agents. This addresses the question, “how can we incentivize an expert to truthfully report a belief about a future event?” Examples include probability distributions (via theory of proper scoring rules [18]), statistics such as the mean, median, variance, etc., and finite-valued “statistics” which correspond to multiple-choice questions [23]. We will describe the beautiful convex-analysis characterizations of proper scoring rules [24, 29, 18], extensions to elicitation of statistics, and connections to truthfulness characterizations in general mechanism-design settings (“why is consumer surplus always a convex function of type?”). A variety of algorithmic game theory examples are mentioned including complexity, auction theory, and human computation.  

Part two covers recent connections to machine learning. We will see that empirical risk minimization (ERM), the dominant algorithmic paradigm in machine learning, can be understood in terms of elicitation, including several popular frameworks such as support vector machines and logistic regression. We will give implications from the results in part one, including characterizations of which hypotheses can be learned and what kinds of loss functions produce them, as well as upper and lower bounds on dimensionality of learning problems. This lens naturally suggest many open directions for future research, which are highlighted.  

This will be the first incarnation of this tutorial. We will not assume prior knowledge beyond basic mathematics; we will make frequent use of convex analysis, but include a thorough primer. That said, familiarity with machine learning will complement the material in the second half. 

Motivation. Many in the EC community, especially from computer science backgrounds, are not yet familiar with proper scoring rules and other elicitation tools or the deep convex-analytic theory underlying them. In this tutorial, not only may they enjoy the elegant theory, but they may also find uses for these tools in their own work. They already appear wide variety of algorithmic game theory applications, particularly in human computation domains such as gold-standard mechanisms [17, 30, 31], peer prediction [32, 33, 16], and prediction and decision markets [19, 20, 8, 7, 26, 1], but also increasingly in mechanism design [6, 12].  

Meanwhile, there is ever-increasing interest in machine learning in the EC community (and vice versa). Hence, we feel that it is valuable to highlight the relationships between the theory of elicitation and fundamental questions and techniques in machine learning. For example, the phrase “proper scoring rule” in the EC community directly translates to “Bregman divergence” in machine 

*Be sure to also check out the prediction markets tutorial, which will build on some of the material in this one.
learning, a concept which shows up in clustering methods, online learning, and basic classification techniques. Beyond celebrating these fascinating connections, we believe that interested researchers can gain insights into machine learning via an economic lens: even the basic concept of a loss function in machine learning can be viewed as a financial penalty.

Beyond this interest, recent work on the connection between elicitation and learning has been fruitful for both camps; see for example [2, 16]. In fact, the recent work in [10, 14, 11] takes insights from economics, applies them to machine learning, and the results in turn apply back to economics in the form of new regression procedures for evaluating the risk measure estimates of banks and other financial institutions. This is a very exciting time to work in this intersection, as we believe that breakthroughs will continue to unfold by applying insights from such a classical “EC topic” to machine learning. There are a variety of open problems and very recent trends that many in the EC community may be interested in exploring.

**Summary of part one.** We will begin with a brief summary of the history, motivation, and definition of proper scoring rules [5, 24, 29, 18]. We will then briefly cover the mathematical prerequisites, namely, convexity of sets and functions, subgradients and Bregman divergences, and perhaps (briefly) convex duality. Then, we will give the fundamental characterization of proper scoring rules in terms of convex functions [24, 29, 18] and give the geometric picture for the proof. Time permitting, we will give an example or two of how scoring rules and this characterization can be useful in e.g. mechanism-design problems [6], complexity theory [3], and crowdsourcing [25]. We will also mention the theory of “generalized truthfulness” in which both the above characterization and Myerson’s characterization of truthful single-item auctions are special cases [12].

We will then move on to eliciting properties (rather than full distributions) [22, 23, 21, 13]. We will discuss elicitation complexity: What must the dimensionality of a prediction be in order to elicit a particular property? For instance, we will see that the variance of a distribution cannot be elicited via a report of a single scalar. Due to time constraints, we will suppress many technical details of the latter material in favor of an overview of open problems and directions in this area.

**Summary of part two.** We will begin with an extremely brief description of the standard statistical learning setting, empirical risk minimization (ERM). We then highlight the correspondence with the property elicitation problem of part one, namely, loss functions correspond to scoring rules and hypotheses correspond to properties.

A nice introduction to this connection is showing how a celebrated result characterizing surrogate loss functions for classification, covering SVMs, logistic regression, and a host of other techniques, can be thought of as characterizing scoring rules for the mode of a distribution [4]. Recent work of Agarwal and Agarwal shows many other such connections [2], some of which are just as accessible. We will also give a simple argument why elicitation, which strictly speaking speaks only of a single distribution on the “y”, can be applied to regression/classification problems where the data comes in (x, y) pairs; under a standard assumption (“Bayes in class”), the hypothesis chosen by ERM is exactly determined by what statistic is elicited by the loss.

Beyond these initial connections, we will focus on the dimensionality of learning problems; for instance, to fit a hypothesis to the conditional variances of a data set via ERM, it is necessary to use at least 2 regression parameters. We will show how the material in part one translates to regression/classification procedures, and how some existing procedures can be recast in light of elicitation, e.g. “superquantile regression” [28, 27, 15]. Again, our treatment of these more advanced questions will focus less on technical details and more on an overview of the frontier for future work.
Bios. Rafael Frongillo (bass, 5’11”) is an assistant professor of computer science at the University of Colorado Boulder. His thesis, *Eliciting Private Information from Selfish Agents*, was obtained in 2013 at the University of California at Berkeley advised by Christos Papadimitriou (bass, 6’1”). He also spent time as a postdoctoral researcher at Microsoft Research New York and Harvard University’s Center for Research, Computation, and Society and EconCS group.

Bo Waggoner (baritone, 5’7”) is a doctoral candidate in computer science at Harvard University, advised by Yiling Chen (alto, 5’5”). His research focuses on the value and elicitation of information in mechanism-design settings. Some organization and choice of content of this tutorial are inspired by the class currently taught by Yiling and Bo at Harvard.

https://canvas.harvard.edu/courses/9622/pages/schedule

References


