# Project Proposal: CS281, Fall 2017

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## 1 Problem Statement

### 1.1 Peer Prediction

The general problem of peer prediction concerns creating mechanisms to incentivize honest forecasts and feedback from crowd workers. The main line along which peer prediction tasks are split is "ground truth" vs. "no ground truth". In scenarios with ground truth, there are methods such as "gold standard reports" which may often be used to conclusively determine effort and quality of reports, but these may be too costly to generate. In scenarios with no ground truth, we often have no better option than to use manipulations on the reports themselves to determine the quality of the other reports.

However, the no ground truth problem inherently prohibits many peer prediction mechanisms, as diversity of opinions will be interpreted as incorrectness. For example, if we were to judge the quality of Google reviews by whether the reports agreed with other Google reviews, truthful minority opinions would be penalized. This leads us to believe that a more complicated heterogeneous-user mechanism is required.

### 1.2 Forecasting

Peer prediction can also be used to provide intermediate feedback in forecasting tasks where there is a true answer that will eventually be realized but is not yet available. This potentially incentivizes workers to invest more effort and allows them to hone their skills. Witkowski et al. [2017] show that proxies can often be generated that closely track the performance of the eventual result. (It remains to be seen whether providing this feedback concurrently with ongoing predictions would affect those predictions, but this is a possible question for our research to explore through simulations such as those in Shnayder et al. [2016b].) We hope to find whether machine learning algorithms can correctly identify "types" of people, based perhaps on measures of general or topic-specific expertise as well as psychological markers and use these types to generate feedback that would lead to improved accuracy and while not penalizing diversity of opinions.

### 1.3 Data

We will primarily be using data from the Good Judgment Project, available online at `https://dataverse.harvard.edu/dataverse.xhtml?alias=gjp`. We hope to then be able to extrapolate results to a new iteration of this forecasting competition, available at `http://gjopen.com`, from which data is being scraped. Unique challenges in this problem include the difficulty of quantifying the underlying variable, identifying the proper grouping mechanism such that people are suitably similar to their peers without encountering extreme sparsity of data, and creating a mechanism that would encourage higher accuracy but not promote herding behavior in an online setting.

## 2 Approach

We will be writing code

## 3 Evaluation

Other peer prediction mechanisms that have been used in similar scenarios and could be used as baselines include Correlated Agreement [Shnayder et al., 2016a], Output Agreement [Von Ahn and Dabbish, 2004], and RF15 [Radanovic and Faltings, 2015], among others.

## 4 Collaboration Plan

Brian Hentschel:
Sophie Hilgard:
Casey Meehan:

## 5 Double Dipping

Brian, Casey: N/A.
Sophie: I have discussed combining my CS281 final project and my research with David Parkes and have his approval.

## References

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