Personalized Peer Truth Serum for Eliciting Multi-Attribute Personal Data

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Motivation

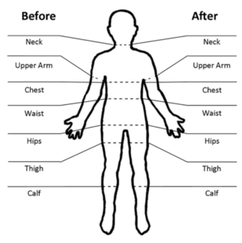
Incentives for Personal Data Elicitation

- Multi-attribute personal data is highly useful for not only supervised and unsupervised machine learning applications but also for various exploratory analysis.
- The applications are only as good as the quality of the data used.
- Incentives are necessary to elicit effort and collect high quality data from a crowd.
- Personal data can't be verified, which makes it very challenging to design incentive mechanisms.
- Peer consistency mechanisms incentivize workers if crowdsourcing tasks can be shared among workers but tasks involving personal data can't be shared.

Examples of Personal Data

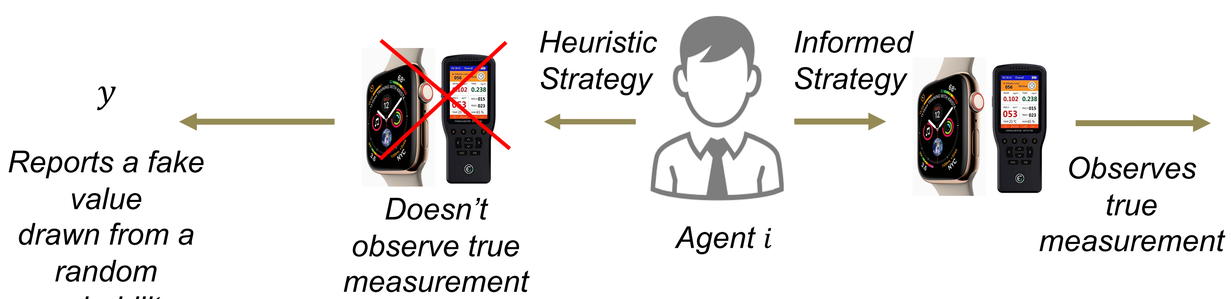
Health Data

Body Measurements



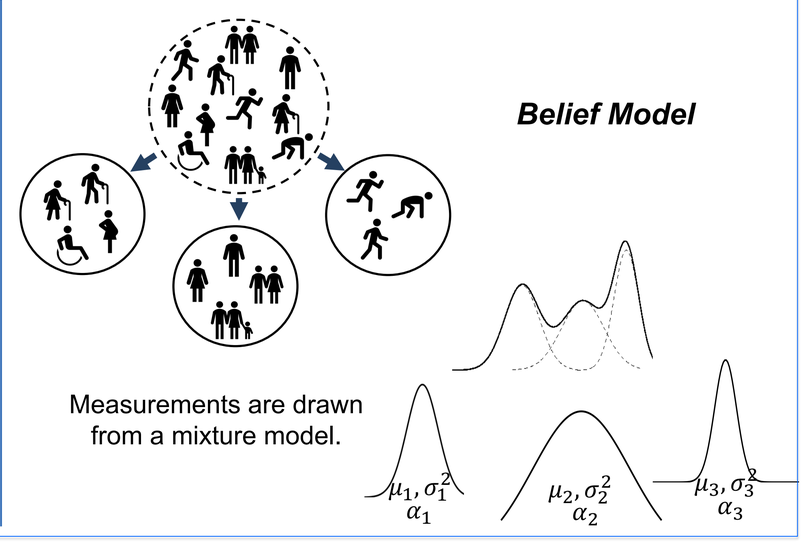
Smart Homes

The Setting



Incentive Mechanism Design Goal

Admit truthfulness
(informed strategy with identity mapping, $y = x$)
as (focal) equilibrium strategy.



The PPTS Mechanism

- The center collects reports from all the workers for all the attributes.
- Let there be a black box oracle that uses the reports submitted by the workers to assign them to their true clusters.
- For each attribute j, the mechanism calculates the attribute score for an agent i using the following formula:

$$r_{ij} = \ln \frac{f(y \mid \hat{\mu}_{L_{ij}}, \widehat{\sigma^2}_{L_{ij}})}{\sum_{k=1}^{K} \widehat{\alpha_k} \cdot f(y \mid \hat{\mu}_{L_{kj}}, \widehat{\sigma^2}_{L_{kj}})}$$

where,

- f is the Gaussian function.
- $\widehat{\alpha_k}$ is the estimated mixing probability of the k^{th} cluster.
- $\hat{\mu}_{L_{kj}}, \widehat{\sigma^2}_{L_{kj}}$ are the maximum likelihood estimates of the mean and standard deviation of k^{th} cluster.

- Agent i finally gets a cumulative reward equal to the average of attribute scores r_{ij} for all attributes $j \in \{1,2 \ldots d\}$.

Properties

Theorem 1 : The PPTS mechanism is Bayes-Nash incentive compatible with strictly positive expected payoffs in the truthful reporting strategy equilibrium.

Theorem 2 : In the PPTS mechanism, the heuristic reporting equilibria result in zero expected payoffs.

Theorem 3 : In the PPTS mechanism, an equilibrium strategy profile defined by a function $g(x) = ax + b$ is not in expectation more profitable than the truthful strategy.

Theorem 4 : The ex-ante expected score of a truthful agent is equal to the conditional mutual information (CMI) of the attribute measurements and the personal factors given the global factors.

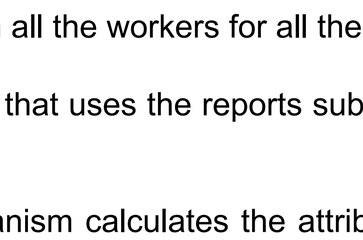
Definition 1 : A clustering algorithm is called ϵ-correct if, given true reports, it assigns a true report to a wrong cluster with probability at most ϵ and ϵ is such that as number of agents $\to \infty$, the MLE estimates $\hat{\mu}_{L_{kj}}, \widehat{\sigma^2}_{L_{kj}}$ converge to $\mu_{L_{kj}}, \sigma^2_{L_{kj}}$ and $\widehat{\alpha_k}$ converges to α_k.

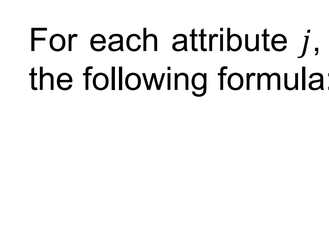
Theorem 5 : Given an ϵ-correct clustering algorithm, the PPTS mechanism is Bayes-Nash incentive compatible even if the clusters are estimated from the reports.

Simulations

Datasets

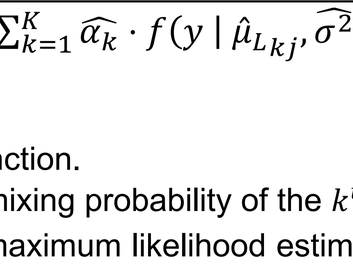
Body Measurements Dataset: 21 body measurements of 507 individuals.





Seed Dataset: 7 measurements of 210 seeds of wheat.

Air Quality Dataset: 852 hourly averaged responses from an array of 5 metal oxide chemical sensors.



Simulated Strategies*

(* See paper for details)

TR - All report truthfully.
RA - All report randomly.
R - Agent i reports randomly.
GS - Agents collude on a Gaussian.