Information Collection and Reporting through Strategic Agents

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Quantifying Uncertainty: Stochastic, Adversarial, and Beyond
@ Simons Institute
Economics of Statistics

- Statistics, based on decision theory, does not explicitly account for:
  - incentive problems
  - strategic behavior

Talk overviews game theory models of:
- data collection
- information reporting

Implications for regulation
Economics of Statistics

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- Implications for regulation
Plan

Data: HARD information

1. Strategic sample selection
   selective disclosure in “hard” data reporting

2. Persuasion bias
   optional stopping in data collection
Plan

Data: HARD information
1. Strategic sample selection
   selective disclosure in “hard” data reporting

2. Persuasion bias
   optional stopping in data collection

Predictions: SOFT information
3. Forecasting contest
   competition for best record

4. Reputational forecasting
   reputation for accurate information
Impact of Sample Selection on Value of Information

Di Tillio-Ottaviani-Sørensen (EMA, 2021)

- Biased researchers in *observational studies*:
  - select sample non randomly from larger presample
  - choose *specification*
  - omit controls
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- How does sample selection affect the value of information?
Impact of ANTICIPATED Selection

- Compare information value of two experiments:
  - Random: \( X = \theta + \varepsilon \) with \( \varepsilon \sim F \) [BLUE]
  - Selected: max of \( k \) iid draws: \( Y = \theta + \varepsilon_k \) with \( \varepsilon_k \sim F^k \) [RED]
“§101 ... A person not knowing how the data were analysed and whom the experimenter told the result of that analysis concerning the system ... but not how many attempts he made to achieve that result, is unable to judge with a determined chance of error whether the chances ... are equal or not...”

“... However, unsuccessful tests usually leave no traces; the public only knows the results which the experimenter thought to be deserving notice. It follows that a person alien to the testing is absolutely unable to regulate bets on whether the result is, or is not attributable to anomalies of chance.”
Here we illustrate idea for **simple hypothesis testing**:

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<tr>
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$\theta_L < R < \theta_H$, prior $p = \Pr(\theta_H)$
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- Location experiment $x = \theta + \varepsilon$, with $\varepsilon \sim F$ independent from $\theta$
  - Assume **logconcave** density $f \Leftrightarrow$ monotone likelihood ratio property
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- Location experiment $x = \theta + \varepsilon$, with $\varepsilon \sim F$ independent from $\theta$
  - Assume **logconcave** density $f \iff$ monotone likelihood ratio property

- With a single draw, cutoff rule optimal: accept iff

  \[ \frac{f(x - \theta_H)}{f(x - \theta_L)} \geq \frac{1 - p}{p} \frac{R - \theta_L}{\theta_H - R} \iff x \geq \bar{x} \]
Random Experiment
Selected Experiment

\[ F^k(x - \theta_L) \quad \text{FP} \]
\[ F^k(x - \theta_H) \]

\[ \theta_L \quad \tilde{x} \quad \theta_H \]

\[ F_N \]
Random v. Selected

\[ FP \{ \]

\[ FN \{ \]

\[ \tilde{x} \]
Random v. Selected

\[ \begin{align*}
\text{FP} \left\{ \begin{array}{c}
\text{FN} \\
\end{array} \right. \\
\tilde{x}
\end{align*} \]
Random v. Selected

\[ 1 - F^k(\bar{y} - \theta_L) = 1 - F(\bar{x} - \theta_L) \quad \Rightarrow \quad \bar{y} = (F^k)^{-1} F(\bar{x} - \theta_L) + \theta_L \]

Using cutoff \(\bar{y}\) in \(Y\) that matches False Positives

Are False Negatives reduced? Yes, with \(F\) normal! More generally?
Random v. Selected

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\[ F^k(\bar{y} - \theta_H) \leq F(\bar{x} - \theta_H) \]

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\[ \Leftrightarrow F^k \text{ is less dispersed than } F \text{ ie } (F^k)^{-1}(q) - F^{-1}(q) \downarrow q \]
Dispersion of Selected Experiment

When is $F^k$ steeper than $F$ at same quantile?
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Theorem (general sample size $n$): Fixing sample size $n$, as pre-sample size $k$ increases, experiment becomes more (less) informative in every monotone problem if reverse hazard rate RHR $f(x|\theta)/F(x|\theta)$ is log-supermodular (log-submodular, w/ support unbounded above)

\[
\frac{f(x|\theta')/F(x|\theta')}{f(x|\theta)/F(x|\theta)} \quad \text{increasing (decreasing) in } x, \text{ for all } \theta' > \theta
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  - **Beneficial** selection: logconcave RHR $\frac{f(x)}{F(x)}$ (e.g., Normal)
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- **Neutral** selection: loglinear RHR $\frac{f(x)}{F(x)}$ (Gumbel)
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  - **Neutral** selection: loglinear RHR $f(x)/F(x)$ (Gumbel)
  - **Harmful** selection: logconvex RHR $f(x)/F(x)$ (e.g., Exponential)
NEUTRAL Selection: Loglinear $f / F$

Gumbel noise: $F(\varepsilon) = e^{-e^{-\varepsilon}}$
HARMFUL Selection: \( f \) LESS Logconcave than \( F \)

Exponential noise: \( F(\varepsilon) = 1 - e^{-\varepsilon} \)
BENEFICIAL Selection: $f$ MORE Logconcave than $F$

Normal noise: $\epsilon \sim \mathcal{N}$
Plan

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1. Hypothesis testing with selected data
   - selection benefits/harms if data has thinner/thicker tail than Gumbel
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Data: HARD information

1. Hypothesis testing with **selected data**
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2. Wald **persuasion games** with costly information collection
   - optional stopping in data collection
Informer benefits from approval of drug with uncertain efficacy

- Evaluator = FDA regulator

$$\theta_e^H > 0$$ in state $H$ and $$\theta_e^L < 0$$ in state $L$
Research and the Approval Process
Henry-Ottaviani (AER, 2019)

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- Informer sequentially acquires & diffuses costly information
  - instantaneous trial result from state-dependent Brownian motion
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    \[ \nu_i > 0 \]
- Informer sequentially acquires & diffuses costly information
  - instantaneous trial result from state-dependent Brownian motion
- Evaluator has coarse instruments for regulation
  - approve/reject, ask for additional evidence [impose liability]
Organizational Deconstruction of Wald

TWO players:

1. Informer \(i\)
   a. directly **controls information** acquisition & pays info cost
   b. but **always wants approval** and does not directly value info
Organizational Deconstruction of Wald

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Wald’s **social planner** $w$

a. controls **all decisions** (rejection/approval) & info acquisition
b. obtains **total payoff** $v_w = \theta_e + v_i$ (evaluator+informer) & pays info cost
Wald Welfare Benchmark: Value Function

![Graph showing the Wald Welfare Benchmark: Value Function with two curves labeled 'Standalone' and 'Immediate approval'. The graph plots the value function against the parameter θ. Key points marked are S*, θ, and S*.](image-url)
Organizational Deconstruction of Wald

- Planner (Wald): \( \max_{s,S} u_w = u_e + u_i \)

\[ s = b_w(S) \land S = B_w(s) \]
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- Planner (Wald) $w$: \[
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- Instead, our players \( i \) and \( e \) solve **constrained Wald problems**
  - with split payoffs & decision rights
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- Compare **organizations** = extensive forms of Wald persuasion games
  1. **Informer \( i \) Authority:**
     - Informer \( i \) max \( u_i|_S \) given evaluator’s approval standard \( S: \) so \( s = b_i(S) \)
     - Evaluator approves for \( q \geq \hat{q}_e = \frac{-\theta^L_e}{\theta^H_e - \theta^L_e} = \frac{\text{Neg Ext}}{\text{Pos Ext} + \text{Neg Ext}} \Rightarrow S = \hat{q}_e \)
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  2. **No Commitment**: informer \( \max_{s} u_i|_S \) & evaluator \( \max_{S} u_e|_S \)

\[
s = b_i(S) \quad \& \quad S = B_e(s)
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Organizational Deconstruction of Wald

- Planner ($Wald$) $w$: $\max_{s, S} u_w = u_e + u_i$
  
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  2. No Commitment: informer $\max_s u_i|_S$ & evaluator $\max_S u_e|_S$
     
     $s = b_i(S) \ & \ S = B_e(s)$

  3. Evaluator $e$ Commitment: $\max_S u_e|_{s=b_i(S)}$
1. Informer Authority Game

Informer Best Reply [RED]

\[ i \text{'s best reply RED } s = b_i(S) \text{ given } S \]

\[ s \text{ on horizontal axis} \]

\[ i \text{ TOP: Informer stops as soon as evaluator persuaded: } s_i = \hat{q}_e \]

\[ i \text{ BOTTOM: Informer withdraws when pessimistic enough: } s_i = b_i(\hat{q}_e) \]
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Informer Best Reply [RED]

- \( i \)'s best reply RED \( s = b_i(S) \) given \( S \) [\( s \) on horizontal axis]
  - locus of horizontal tangencies of iso-payoff curves PINK
  - \( b_i(S) \uparrow S \): LOSS OF CONTROL
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- $i$ expects $e$ to adopt for $q \geq S$ [S on vertical axis]
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- **BOTTOM**: Informer withdraws when pessimistic enough: $s^i = b_i(\hat{q}_e)$
Comparison to Kamenica-Gentzkow’s (2011) commitment solution?
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We recover KG without info frictions if (1) $c \to 0$ & (2) $r \to 0$, so:

- KG solution becomes **sequentially optimal** without commitment
2. No-Commitment “Nash” Outcome

- **Evaluator** gains commitment power: precursor of FDA in 1905
2. No-Commitment “Nash” Outcome

- **Evaluator** $e$ gains commitment power: precursor of FDA in 1905
- **EQUILIBRIUM**: Stationary Markov Perfect Equilibrium solving
  - $i$ controls withdrawal standard: $s^N = b_i(S^N)$ RED
  - $e$ controls adoption standard: $S^N = B_e(s^N)$ BLUE
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- $e$ sets **more stringent** approval standard: $S^N > S^i$
2. No-Commitment “Nash” Outcome

- **Evaluator** \( e \) **gains commitment power**: precursor of FDA in 1905
- **EQUILIBRIUM**: Stationary Markov Perfect Equilibrium solving
  - \( i \) controls withdrawal standard: \( s^N = b_i(S^N) \) RED
  - \( e \) controls adoption standard: \( S^N = B_e(s^N) \) BLUE

- \( e \) sets more stringent approval standard: \( S^N > S^i \)
- \( i \) withdraws earlier: \( s^N > s^i \)
Evaluator commits ex ante to approval when belief reaches $S^e$

- approve iff $q \geq S^e$
3. Evaluator Commitment Solution

- Evaluator commits ex ante to approval when belief reaches $S^e$
  - approve iff $q \geq S^e$
- Stackelberg tangency with $e$’s BLUE iso-payoffs
- Evaluator **benefits** to be more lenient $S^e < S^N$
  - commits to free-ride less to encourage more info collection
- Compared to Nash, **FALSE POSITIVES** ↑ & **FALSE NEGATIVES** ↓
Plan

Data: HARD information

1. Hypothesis testing with **selected data**
   - anticipated selection benefits/harms if data has thinner/thicker tail than Gumbel

2. Wald persuasion games with costly information collection
   - equilibrium persuasion: bias from optional stopping
   - tolerate false positives to encourage info collection
Plan

Data: HARD information

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Predictions: SOFT information

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   - excessive differentiation

2. **Reputational** forecasting
   - conformism with naive audience
   - information loss with rational audience
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Honest Forecasting: Benchmark Statistical Model

- Unknown state with prior \( x \sim \mathcal{N}(\mu, \frac{1}{\nu}) \)
- Single forecaster with private signal \( s \) about state \( x \)
- Honest forecaster (naive statistician) minimizes forecast error

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\min_m \mathbb{E} \left[ (m - x)^2 \middle| s \right]
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- Best statistical forecast is posterior expectation
  \[
  m = E [x | s]
  \]
  - Forecasts are orthogonal to the forecast error
  - Forecasts are dispersed, but less than the state
Forecasting Contest

Ottaviani-Sørensen (2006, J of Financial Economics)

Francis Galton’s (1907) ox weight competition:
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2. Forecasters simultaneously submit forecasts $m_i$
3. True state is publicly observed $x$
4. Forecaster whose forecast is closest to the state wins
At the posterior expectation

\[ m_i = E \left[ x \mid s_i \right] \]

A small deviation away from the prior mean \( \mu \) results in

- A second-order loss due to lower chance of winning, but
- A first-order gain due to reduced competition
Excessive Differentiation in Forecasting Contest

Figure: Equilibrium forecasts are more variable than posterior expectation
Reputational Cheap Talk

Ottaviani-Sørensen (2006, RAND J Economics)

1. Single forecaster observes signal \( s \) with accuracy \( t \)
Reputational Cheap Talk

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$$E[t|m, x]$$
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- Objective of forecaster is to obtain **favorable evaluation** $E[t|m,x]$
  - Forecast $m$ is a (cheap talk) signal
  - **Is honest** $m = E[x|s]$ **an equilibrium?**
Misreporting Incentives

- If evaluator (naïvely) expects honest forecasting $m = E[x|s]$
  - Will forecaster want to report honestly?
Misreporting Incentives

- If evaluator (naïvely) expects honest forecasting $m = E[x|s]$
  - Will forecaster want to report honestly?
- With location signal, forecaster has **incentive to lie** reporting $E[x|\hat{s} = E[x|s]]$,
Reputational Cheap Talk Equilibrium

- Equilibrium communication is coarse (as in Crawford and Sobel, 1982)
  - Forecasters with signals in an interval send identical message
  - Loss of forecast accuracy!
Reputational Cheap Talk Equilibrium

- Equilibrium communication is coarse (as in Crawford and Sobel, 1982)
  - Forecasters with signals in an interval send identical message
  - Loss of forecast accuracy!

- E.g., there exists a two-message equilibrium:
  - Report whether $s$ is above or below prior mean $E[x]$
Forecasting Summary

► Concern for accuracy leads to:
  ► excessive conformity if the market is naïve
  ► loss of information if the market is rational
Forecasting Summary

- Concern for accuracy leads to:
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- Competition for best accuracy record leads to excessive differentiation
Game Theory of Data Collection & Reporting

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