

Rationalizing Pre-Analysis Plans: Statistical Decisions Subject to Implementability

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Introduction

- Trial registration and pre-analysis plans (PAPs) have become a standard requirement for experimental research.
 - For clinical studies in medicine starting in the 1990s.
 - For experimental research in economics more recently.
- Standard justification: Guarantee validity of inference.
 - P-hacking, specification searching, and selective publication distort inference.
 - Tying researchers' hands prevents selective reporting.
 - "PAPs are to frequentist inference what RCTs are to causality."
- Counter-arguments:
 - Pre-specification is costly.
 - Interesting findings are unexpected and flexibility is necessary.

Open questions

1. Why do we need a commitment device?
Standard decision theory has no time inconsistency!
2. Under what conditions are PAPs more or less useful?
How do we trade off the benefits and costs of PAPs?
3. How should the structure of PAPs look like?

Our approach

- Import insights from contract theory / mechanism design to statistics.
 - PAPs can be rationalized with multiple parties, conflicts of interest, and costly communication / asymmetric information.
 - We consider (optimal) statistical decision rules subject to the constraint of implementability.
- Our model:
 1. A decision-maker commits to a decision rule,
 2. then an analyst commits to a PAP,
 3. then observes the data, reports selected statistics to the decision-maker,
 4. who then applies the decision rule.
- PAPs are optimal when
 - there are many analyst degrees of freedom,
 - and/or communication costs are high.

Alternative interpretations of our model

1. Publication decision:

- A researcher wants to get published.
- A journal wants to publish only studies for large enough true effects.

2. Drug approval:

- A pharma company wants drug approval.
- The public authority (FDA) wants to approve only effective drugs.

3. Hypothesis testing:

- A researcher wants to always reject the null.
- A reader wants to only reject when the null is false.

Literature

- **P-hacking and publication bias**

Ioannidis (2005); Gelman and Loken (2013); Andrews and Kasy (2019)

- **Contract theory and mechanism design**

Hurwicz (1972); Glazer and Rubinstein (2004); Kamenica and Gentzkow (2011); Kamenica (2019)

- **Discussions of PAPs by empirical practitioners**

Food and Drug Administration (1998); Coffman and Niederle (2015); Olken (2015); Christensen and Miguel (2018); Duflo et al. (2020)

- **Applied theory of research and the publication process**

Chassang et al. (2012); Tetenov (2016); Ottaviani et al. (2017); Di Tillio et al. (2017); Spiess (2018); Henry and Ottaviani (2019); McCloskey and Michailat (2020); Libgober (2020); Yoder (2020); Williams (2021); Abrams et al. (2021); Viviano et al. (2021); Banerjee et al. (2020); Frankel and Kasy (2021); Andrews and Shapiro (2020)

Introduction

Baseline model

- Assumptions
- Implementability and optimality

Analysis

- A minimal example: $\bar{n} = 3$
- Symmetric publication rules
- General solution

Model variations

- Frequentist testing
- Multiple parameters / hypotheses
- Analyst private information

Conclusion

Setup

- Two agents: Decision-maker and analyst.
- The analyst observes a vector

$$\mathbf{X} = (X_1, \dots, X_{\bar{n}}),$$

where

$$X_i \stackrel{\text{iid}}{\sim} \text{Ber}(\theta).$$

- Analyst: Reports a subvector \mathbf{X}_I to the decision-maker, where

$$I \subset \{1, \dots, \bar{n}\}.$$

- Decision-maker: Makes a decision

$$\mathbf{a} \in \{0, 1\},$$

based on this report.

Prior and objectives

- Common prior:

$$\theta \sim \text{Beta}(\alpha, \beta).$$

- Analyst's objective:

$$u^{\text{an}} = a - c \cdot |I|.$$

$|I|$ is the size of the reported set,

c is the cost of communicating an additional component.

- Decision-maker's objective:

$$u^{\text{d-m}} = a \cdot (\theta - \underline{\theta}).$$

$\underline{\theta}$ is a commonly known parameter.

Minimum value of θ beyond which the decision-maker would like to choose

$a = 1$.

Timeline

1. The decision-maker commits to a decision rule

$$\mathbf{a} = \mathbf{a}(\mathbf{J}, l, \mathbf{X}_l).$$

2. The analyst reports a PAP

$$\mathbf{J} \subseteq \{1, \dots, \bar{n}\}.$$

3. The analyst next observes \mathbf{X} , chooses $l \subseteq \{1, \dots, \bar{n}\}$, and reports

$$(l, \mathbf{X}_l).$$

4. The decision rule is applied and utilities are realized.

Implementability

- Let x denote values that the random vector \mathbf{X} may take.
- Reduced form mapping (statistical decision rule)

$$x \mapsto \bar{a}(x).$$

- $\bar{a}(x)$ is implementable
if there exist mappings $l(x)$ and $a(l, x_l)$
such that for all x

$$\bar{a}(x) = a(l(x), x_{l(x)}),$$

and

$$l(x) \in \operatorname{argmax}_l a(l, x_l) - c \cdot |l|.$$

Optimal implementable publication rules

- The latter is the incentive compatibility constraint, which implies

1.

$$I(\mathbf{x}) \in \underset{I}{\operatorname{argmin}} \{ |I| : \mathbf{a}(I, \mathbf{x}_I) = \mathbf{1} \}$$

whenever $\bar{\mathbf{a}}(\mathbf{x}) = \mathbf{1}$, and $I(\mathbf{x}) = \emptyset$ else.

2.

$$|I(\mathbf{x})| \leq 1/c$$

for all \mathbf{x} .

- Our agenda:
 - Find implementable mappings (decision rules) $\bar{\mathbf{a}}(\mathbf{x})$
 - that maximize the expected decision-maker utility $E[\mathbf{u}^{\text{d-m}}]$.

Notation

- Successes among all components: $\mathbf{s}(X) = \sum_{i=1}^{\bar{n}} X_i$.
Successes among the subset I : $\mathbf{s}(X_I) = \sum_{i \in I} X_i$.

- Maximal number of components the analyst is willing to submit:

$$\bar{n}^{PC} = \max \{n : 1 - cn \geq 0\} = \lfloor 1/c \rfloor .$$

- First-best cutoff for the decision-maker:

$$\underline{\mathbf{s}}^*(n) = \min \{ \underline{\mathbf{s}} : E[\theta | \mathbf{s}(X_1, \dots, n) = \underline{\mathbf{s}}] \geq \underline{\theta} \} .$$

- Minimal cutoff for the decision-maker:

$$\underline{\mathbf{s}}^{min}(n) = \min \{ \underline{\mathbf{s}} : E[\theta | \mathbf{s}(X_1, \dots, n) \geq \underline{\mathbf{s}}] \geq \underline{\theta} \} .$$

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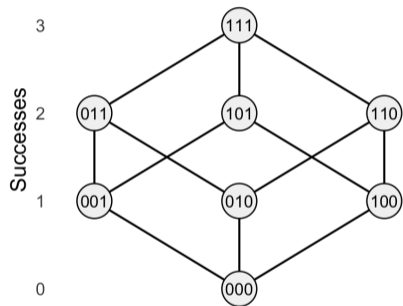
- Frequentist testing
- Multiple parameters / hypotheses
- Analyst private information

Conclusion

A minimal example: $\bar{n} = 3$

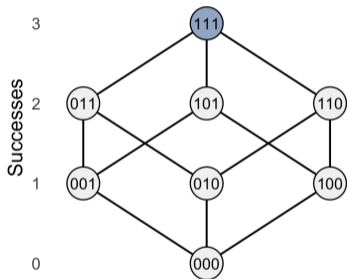
- Suppose $\bar{n} = 3$.
Possible realizations of \mathbf{X} form a cube.
- Vertical axis =
number of successes $\mathbf{s}(\mathbf{X})$.
- Suppose $\bar{n}^{PC} = 2$.
Possible reports $(I, \mathbf{X}_I) \cong$
edges of the cube.
- Reduced form mappings $\bar{\mathbf{a}}(\mathbf{x}) \cong$
set of nodes for which $\mathbf{a} = 1$.

Possible realizations of \mathbf{X}

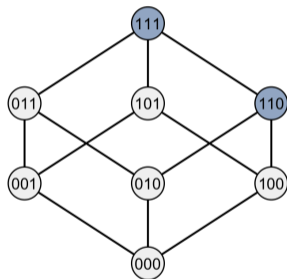


A minimal example: $\bar{n} = 3$

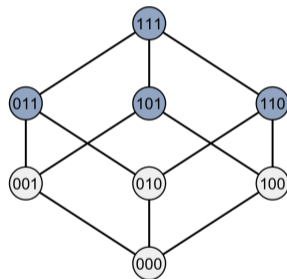
Infeasible rule



Pre-analysis plan



Symmetric cutoff rule



A minimal example: $\bar{n} = 3$

Case I: Symmetric cutoff rule is optimal

- Suppose $\bar{n} = 3$, $\bar{n}^{PC} = 2$, and $\underline{s}^*(3) = 2$.
- The **unconstrained efficient** solution is given by

$$\bar{a}(X) = \mathbf{1}(s(X) \geq 2).$$

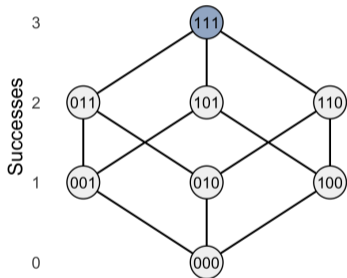
- This solution **can be implemented** by

$$a(l, X_l) = \mathbf{1}(s(X_l) \geq 2).$$

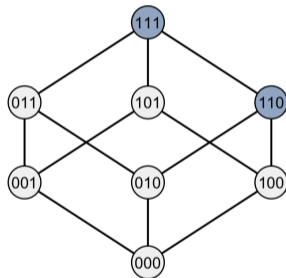
- **No PAP** is needed to implement this solution.

A minimal example: $\bar{n} = 3$

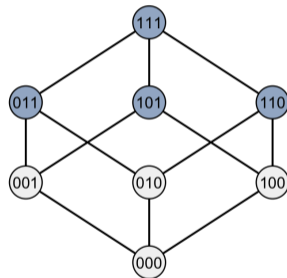
Infeasible rule



Pre-analysis plan



Symmetric cutoff rule



A minimal example: $\bar{n} = 3$

Case II: PAP is optimal

- Suppose again that $\bar{n} = 3$, and $\bar{n}^{PC} = 2$. Suppose now

$$\underline{s}^*(3) = 3, \quad \underline{s}^*(2) = 2$$

- The **unconstrained efficient** solution is given by

$$\bar{a}(X) = \mathbf{1}(s(X) = 3).$$

There is **no** incentive compatible **implementation** of this solution.

- The **PAP** solution for $J = \{1, 2\}$,

$$a(J, I, X_I) = \mathbf{1}(I = \{1, 2\}, s(X_I) = 2),$$

yields $E[u^{d-m}] > 0$, and is **constrained optimal**.

Symmetric publication rules

- Denote $t(X_I) = |I| - s(X_I)$.
- Consider now, for general \bar{n} , symmetric rules of the form

$$a(s(X_I), t(X_I)),$$

Lemma (Symmetrically implementable rules)

$\bar{a}(\cdot)$ is a reduced form publication rule that is implementable by such a symmetric rule iff it is of the form

$$\bar{a}(X) = \mathbf{1}(s(X) \in \mathcal{S}),$$

where \mathcal{S} is a union of intervals of length at least $\bar{n} - \bar{n}^{PC}$.

Optimal symmetric rules

Proposition (Optimal symmetric publication rule)

The optimal reduced-form publication rule that is symmetrically implementable takes the form

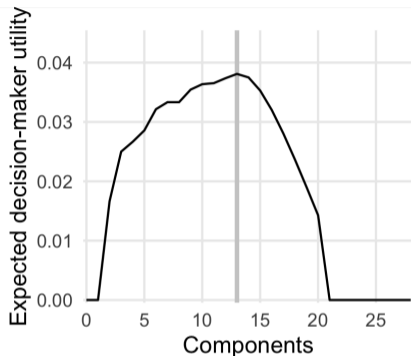
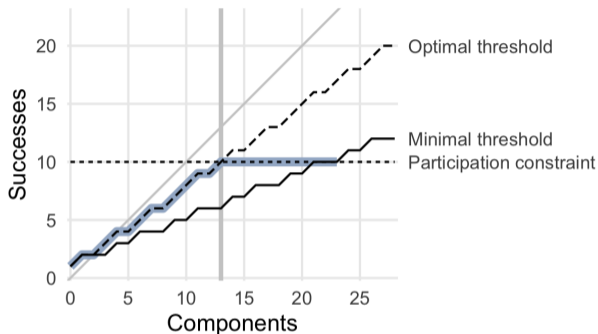
$$\bar{\mathbf{a}} = \mathbf{1}(\mathbf{s}(X) \geq \min(\underline{\mathbf{s}}^*, \bar{n}^{PC})),$$

if $\bar{n}^{PC} \geq \underline{\mathbf{s}}^{\min}$, and can be implemented by

$$\mathbf{a} = \mathbf{1}(\mathbf{s}(X_I) \geq \min(\underline{\mathbf{s}}^*, \bar{n}^{PC})).$$

Otherwise the optimal publication rule is given by $\mathbf{a} \equiv \mathbf{0}$.

Symmetric cutoff without PAP, uniform prior



If the number of components \bar{n} is to the right of the maximum \bar{n}^* :

- PAPs increase decision-maker welfare
- by forcing the analyst to ignore all components $i > \bar{n}^*$.

General implementable rules

Lemma

The implementable publication functions $\bar{\mathbf{a}}(\mathbf{x})$ are exactly those that are of the form

$$\bar{\mathbf{a}}(\mathbf{x}) = \mathbf{1}(\mathbf{x} \in \cup_j \mathbf{C}_{I_j, \mathbf{w}_j}),$$

for some set of $\{(I_j, \mathbf{w}_j)\}$, where $\mathbf{C}_{I, \mathbf{w}}$ are the cylinder sets

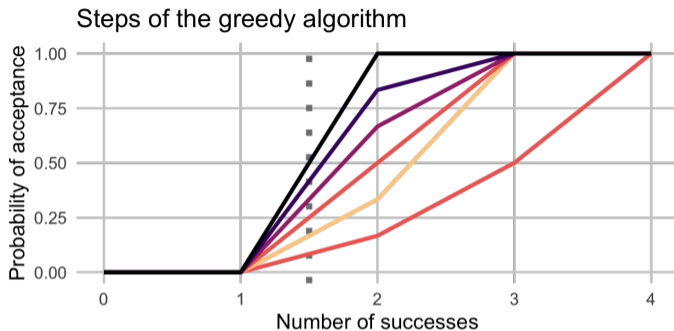
$$\mathbf{C}_{I, \mathbf{w}} = \{\mathbf{x} : \mathbf{x}_I = \mathbf{w}\},$$

and $|I_j| = \bar{n}^{PC}$ for all j .

(Approximately) optimal implementable rules

- Conceptually:
 - Optimal solution is given by the maximizer of $E[\mathbf{u}^{\text{d-m}}]$
 - among the implementable reduced form rules $\bar{\mathbf{a}}(\mathbf{x}) = \mathbf{1}(\mathbf{x} \in \cup_j \mathbf{C}_{I_j, w_j})$.
- This is a hard combinatorial optimization problem!
 - Large number of possible unions of cylinder set.
 - No simplifying properties such as super-modularity.
- Alternatives:
 1. Restricted rules (e.g. cut-off rules with PAPs).
 2. Heuristic optimization algorithms (e.g. greedy optimization).

Greedy algorithm for $\bar{n} = 4, \bar{n}^{PC} = 2, \underline{\theta} = 0.6$



- Each step increases the probability of publication.
- The first step is the PAP solution. The last step is the cutoff solution.
- Hue codes expected decision-maker utility. Step 2 yields the highest utility.

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Model variation I: Frequentist testing

- Setup same as in the baseline model, except for the decision-maker objective:
 - Consider the **null hypothesis** $\theta \leq \underline{\theta}$.
 - $\Rightarrow X_i$ is a valid test for the **significance level** $\underline{\theta}$.

- **First best** rule (uniformly most powerful test):

Critical value $\underline{s}^{test}(\bar{n})$, $U \sim \text{Uniform}([0, 1])$,

$$\bar{a}(X) = \mathbf{1}(s(X) + U \geq \underline{s}^{test}(\bar{n})).$$

- When $\underline{s}^{test}(\bar{n}) > \bar{n}^{PC}$, the first best is **not implementable**.
In this case no cutoff rule exists that

1. controls size, and
2. has non-trivial power.

- **Second best:**

Use PAP to restrict \bar{n} to the largest value such that $\bar{a}(X)$ is implementable.

Model variation II: Multiple parameters / hypotheses

- Setup same as in the baseline model, except for the decision-maker objective:

$$\mathbf{u}^{\text{d-m}}(\mathbf{a}) = \mathbf{a} \cdot \sum_{i \in I} (\theta_i - \underline{\theta}),$$

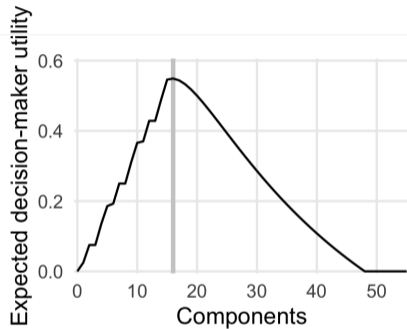
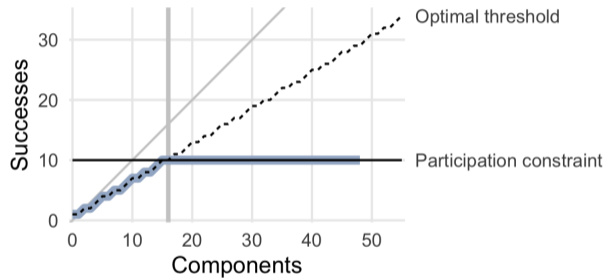
where there are parameters θ_i for every i .

- Joint distribution of data and parameters:

$$\begin{aligned} X_i | \theta_1, \dots, \theta_{\bar{n}}, \bar{\theta} &\sim \mathbf{Ber}(\theta_i) \\ \theta_i | \bar{\theta} &\sim \mathbf{Beta}(m\bar{\theta}, m(1 - \bar{\theta})) \\ \bar{\theta} &\sim \pi, \end{aligned}$$

- Selective reporting distorts inference.
 - For large \bar{n} or \mathbf{c} , the first best is not implementable,
 - but a PAP allows to implement the second best.

Model variation II: Multiple parameters / hypotheses



Model variation III: Analyst private information about signal validity

- Setup same as baseline model, except observability is determined by $\mathbf{W} = (W_1, \dots, W_{\bar{n}})$.
- Before choosing \mathbf{J} , the decision-maker observes \mathbf{W} . After choosing \mathbf{J} , she observes the vector $\mathbf{X}' = (W_1 X_1, \dots, W_{\bar{n}} X_{\bar{n}})$, and reports a subvector of \mathbf{X}' to the decision-maker.
- $\bar{n}' = |\mathbf{W}|$, is common knowledge. The decision-maker's prior over \mathbf{W} given \bar{n}' is uniform over all permutations of the components i .
- Solutions are exactly the same as in the baseline model. except we need the decision-maker (not the decision-maker) to choose the PAP.

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Summary

- Single agent (statistical) decision theory can not rationalize PAPs.
- Mechanism design allows us to study implementable statistical decision rules.
- In our model, PAPs are optimal when
 1. there are many decision-maker degrees of freedom
 2. and communication costs are high.
- Variations of the baseline model: Qualitative conclusions are robust.
 1. Replacing the decision-maker objective by size and power of a statistical test.
 2. Multiple parameters or hypotheses.
 3. Analyst private information about signal validity.
 4. No decision-maker commitment.
 5. Ex-ante uncertainty about the available number of components \bar{n} .
 6. The decision-maker bears the communication cost.

Thank you!