The Model

Introduction

Analysis

Empirical study (MOOCs)

Conclusion

Strong truthfulness in Peer Prediction with Overlapping Tasks

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Joint work with Victor Shnayder and Rafael Frongillo

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Information Elicitation Without Verification

Illustrative examples:

- Participatory sensing
- Emotional response to content
- Consumer surveys
- Algorithm feedback
- Peer grading in MOOCs

Effort is costly. Need to reward informative responses, but without any ground truth; avoid unintended equilibria, collusion.

How to do this?

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Two Kinds	of Mechan	isms		

- Minimal mechanisms : ask agents for information ('signal')
- Non-minimal: ask agents for signal, along with belief about signal of another agent.

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Two Kinds	of Mechani	isms		

Minimal mechanisms : ask agents for information ('signal')

Non-minimal: ask agents for signal, along with belief about signal of another agent.



- Two agents, joint signal distribution $P(X_1, X_2)$
- Signals $i, j \in \{1, \ldots, m\}$
- Take *reports* $\{r_1, r_2\}$, provide payment to each agent:

report
$$r_2$$

1 2
report r_1 2 $\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

(Strict) proper: truthful reporting is a Bayes-Nash equilibrium.

Need $P(X_2 = 1 | X_1 = 1) > P(X_2 = 2 | X_1 = 1)$; and there are uninformative equilibria with greater payment.



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Miller, Resnick and Zeckhauser, 2005:

- Receive report r_1 , and form belief $b_1 = P(X_2|X_1 = r_1)$
- Use proper scoring rule $t_1(b_1, r_2)$

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Problems: (1) designer needs model; (2) uninformative equilibria with greater payment.

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The Peer Prodiction Method					

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Faltings et al. (2012); Witkowski and Parkes (2012):

■ Assume knowledge of *marginal probability*, *P*(*X*)

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Mechanism	n Desiderat	a		

For peer prediction to be used in practice:

- Minimal mechanism
- (Strictly) Proper
- Low knowledge requirements on designer
- Truthful reports maximize expected payments:
 - *Strong-truthfulness* (in case of a tie ⇒ permutation)
 - Informed-truthfulness (in case of a tie ⇒ informed strategy)
- Heterogeneous agents (i.e., qualities, tastes)

Can assume multiple (independent) tasks.

What do we know?	
 Jurca and Faltings, 2009. n ≥ 4 agents, knock-out pure, uninformative equil. Ignore mixed equilibria, binary-signal only, require model. Dasgupta and Ghosh, 2013. Multiple tasks. Strict-proper, strong-truthful. Binary-signal only Radonovic and Faltings, 2015. Multiple tasks. Strict-proper, strong-truthful amongst symmetric strategies. Multi-signal, but results only hold asymptotically, and need homogeneous agents. Kamble et al., 2015. Multiple tasks. Strict-proper, strong-truthful amongst symmetric strategies. Multi-signal, but results only hold asymptotically, and need homogeneous agents. 	ly.

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Multiple tasks (with distinct, known context). Non-binary effort. Optimal effort in unique, DSE. *Multi-signal, but ignore misreports (not strong-truthful, not proper.)*

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Experimen	tal evidenc			

Gao, Mao, Chen and Adams, 2014.

This matters! mTurk experiment (see either collusion, or confusion.)

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Our Contributions: Robust, Multi-Signal Methods

 OA-mechanism. Strict-proper and strong-truthful for multi-signal, categorical domains (generalizes DG'13).

With some domain knowledge:

- 01-mechanism. Informed-truthful and proper for general, multi-signal domains (allow heterogeneity).
- ABCD-mechanism. Strong-truthful (symmetric) for general, multi-signal domains w/ het. Not proper, but all equil strictly worse than truth in large system.

Empirical analysis:

~100 questions across ~30 exercises in 17 MOOCs. Around 325,000 peer-evaluation responses.



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- Agents 1, 2
- Tasks $k (\geq 3)$; Signals $i, j \in \{1, \dots, m\}$ (require effort)
- Joint distribution $P(X_1 = i, X_2 = j)$ (possibly asymmetric)
- Overlapping tasks: shared K_s , agent 1 K_1 , agent 2 K_2 .
- Multi-task peer prediction: for each $k \in K_s$, payment $\{r_1^k, r_2^k, r_1^{K_1}, r_2^{K_2}\} \mapsto \mathbb{R}$
- Strategies: $F_{ir} = P(r_1 = r | X_1 = i)$ $G_{jr} = P(r_2 = r | X_2 = j)$
 - In Informed strategy: $F_{lr} \neq F_{lr}$, some $i \neq j$, some r
 - In Truthful strategy: F^{*}

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Informed strategy: F_{ir} ≠ F_{jr}, some i ≠ j, some r
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Basic Set-up						

- Agents 1, 2
- Tasks $k (\geq 3)$; Signals $i, j \in \{1, \dots, m\}$ (require effort)
- Joint distribution $P(X_1 = i, X_2 = j)$ (possibly asymmetric)
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Introduction	The Model ○●○	Analysis 00000000	Empirical study (MOOCs)	Conclusion
Solution	Concepts			

- *E*(*F*, *G*): *expected payment* for a shared task
- Bayes-Nash equil.
- (Strict) Proper: $E(F^*, G^*) \ge E(F, G^*)$, for all $F \neq F^*$
- Strong-truthful: $E(F^*, G^*) \ge E(F, G)$, for all F, G (tie \Rightarrow permutation); also strict proper
- Informed-truthful: $E(F^*, G^*) \ge E(F, G)$, for all F, G (tie \Rightarrow informed); also proper

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Parameterized by score $S : \{1, ..., m\} \times \{1, ..., m\} \mapsto \mathbb{R}$

- Assign agents to tasks, get reports
- For shared $k \in K_s$, pay both 1 and 2

$$S(r_1^k,r_2^k)-S(r_1^\ell,r_2^m),$$

for $\ell \in K_1$ and $m \in K_2$ (can also take empirical average)

Idea: Reward 'excess agreement' not 'default agreement.'

- Zero payment if say '1' all the time, or random report.
- For *S* as the identify (output-agreement) matrix, this is multi-signal generalization of DG'13.



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Analysis	: Expected	Pavment		

For identity score-matrix:

$$E(F,G) = \sum_{ij} P(i,j) \sum_{r} F_{ir}G_{jr} - \sum_{ij} P(i)P(j) \sum_{r} F_{ir}G_{jr}$$
$$= \sum_{ij} \Delta_{ij} \sum_{r} F_{ir}G_{jr}.$$

Delta matrix:

 $\Delta_{ij} = P(i, j) - P(i)P(j); \text{ if } \Delta_{ij} > 0 \text{ then } P(j|i) > P(j)$

Example: P: $\begin{pmatrix} 0.4 & 0.15 \\ 0.15 & 0.3 \end{pmatrix} \Delta \approx \begin{pmatrix} 0.1 & -0.1 \\ -0.1 & 0.1 \end{pmatrix}$ or, $\begin{pmatrix} + & - \\ - & + \end{pmatrix}$

For general S:

$$E(F,G) = \sum_{ij} \Delta_{ij} \sum_{r_1,r_2} S_{r_1,r_2} F_{ir_1} G_{jr_2}$$
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Introduction	The Model	Analysis ●0000000	Empirical study (MOOCs)	Conclusion 000
Analysis	: Expected	Payment		

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Deterministic Strategies

Lemma 1

Deterministic F, G maximize E(F, G).

$E(F,G) = \max_{F} \max_{G} h(F,G) = \max_{F} OBJ(F),$

where h(F, G) is linear in either argument. Fixing F, opt G is deterministic. OBJ(F) is convex, and opt F is deterministic.

Can focus on deterministic strategies:

- sufficient to prove strong-truthful, or and informed-truthful.
- sufficient to check for deviations from truthful

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Simplified a	analysis			

Deterministic strategies F(i), G(j).

For identity-matrix S:

$$E(F,G) = \sum_{ij} \Delta_{ij} \mathbb{I}(F(i) = G(j))$$

For general score matrix S:

$$E(F,G) = \sum_{ij} \Delta_{ij} S_{F(i),G(j)}$$

The game is to find 'which scores to pick' for each (i,j) pair.

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The OA-N	lechanisn	n		

S is the identity matrix.

Categorical domain:

$$\operatorname{sig}(\Delta):\left(\begin{array}{cc} + & - & - \\ - & + & - \\ - & - & + \end{array}\right)$$

Image labeling {swim, fly, walk}, vs. grading {76, 78, 79, ...}

Theorem 1

The OA-mechanism is strict-proper and strongly-truthful if the world is categorical.

Obtain DG'13 as a corollary. Theorem is tight.

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$$\operatorname{sig}(\Delta): \begin{pmatrix} + & - & - \\ - & + & - \\ - & - & + \end{pmatrix}$$

Image labeling {swim, fly, walk}, vs. grading {76, 78, 79, ...}

Theorem 1

The OA-mechanism is strict-proper and strongly-truthful if the world is categorical.

Obtain DG'13 as a corollary. Theorem is tight.

Introduction	The Model	Analysis ○○○○●○○○	Empirical study (MOOCs)	Conclusion
The $\bigcap A_{-r}$	nochanier	n		

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$$E(F^*, G^*) = \sum_i \Delta_{ii} = \sum_{ij:\Delta_{ij}>0} \Delta_{ij} \ge \sum_{ij} \Delta_{ij} \mathbb{I}(F(i) = G(j)) = E(F, G),$$

for all *F*, *G*. Also need: tie in payment \Rightarrow permutation strategy.

- Case 1: Not permutation, and symmetric. Must be two *i*, *j* $(i \neq j)$ that map to *r*. Assign $\Delta_{ij} < 0$ pair to score $S_{r,r} = 1$. Worsel
- Gase 2: Asymmetric, e.g., agent 1 strategy $i \rightarrow r$, agent 2 strategy $i \rightarrow r'$. Assign $\Delta_{ii} > 0$ pair to score $S_{\alpha r'} = 0$. Worsel

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The OA-mechanism

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Are we done? Let's look at some data.

- Peer-evaluation responses to 100 questions across 30 exercises in 17 MOOCs
- Vast majority of questions have $m \in \{2, 3, 4\}$.
 - Example rubric element: "Not much of a style at all", "Communicative style", and "Strong, flowing writing style".



Introduction 00000000	The Model	Analysis ooooooooo	Empirical study (MOOCs)	Conclusion

$$S_{ij} = \left\{ \begin{array}{ccc} 1 & , \text{ if } \Delta_{ij} > 0 \\ 0 & \text{ o.w.} \end{array} \right. \Delta = \left(\begin{array}{ccc} + & + & - \\ + & + & - \\ - & - & + \end{array} \right) S = \left(\begin{array}{ccc} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right)$$

Theorem 2

For general domains, the 01-mechanism is informed truthful (and proper).

$$E(F^*, G^*) = \sum_{ij} \Delta_{ij} S_{ij} = \sum_{ij:\Delta_{ij}>0} \Delta_{ij} \ge E(F, G), \quad \forall F, G$$

Also need to show uninformed \Rightarrow strictly less payment. Fix G, consider uninformed F (e.g., F(i) = `1', for all i). Have $E(F, G) = \sum_{ij} \Delta_{ij} S_{1,G(j)} < E(F^*, G^*).$

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Introduction 00000000	The Model	Analysis ooooooo●	Empirical study (MOOCs)	Conclusion

Parameterized
$$0 \le a < b < c < d$$

Scores: $S_{ii} = \begin{cases} b & \text{, if } \Delta_{ii} \le 0 \\ c & \text{o.w.} \end{cases}$ $S_{ij} = \begin{cases} a & \text{, if } \Delta_{ij} \le 0 \\ d & \text{o.w.} \end{cases}$

Theorem 3

For general domains, the ABCD-mechanism is strong-truthful amongst symmetric strategies.

Expected payment $E(F^*, G^*) = \sum_{ij} \Delta_{ij} S_{ij}$ Consider a non-permutation, symmetric strategy. Must be *i*, $(i \neq j)$ that map to same *r*. Assigns score $S_{r,r} \in \{b, c\}$ to (*i* and (*j*, *i*), worse because $a < \{b, c\} < d$.

Introduction 00000000	The Model	Analysis ○○○○○○●	Empirical study (MOOCs)	Conclusion
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Delta matri	ices: MOO	C Data		

■ 17 courses, 104 questions, ~325,000 reports.



Positive correlation.

For models of size 4 and 5, see failure of categorical (e.g., score 2 is +ve correlated with score 3.) *Ordinal domain*.

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Delta matr	ices: MOO	C Data		
	1000 100	2x2 Δ matrices		
	3x3 🛆 i	matrices		
			0.10 0.05 0.00	







Introduction	The Model	Analysis 0000000	Empirical study (MOOCs)	Conclusion
Empirical	observat	ions		

All mechanisms are strong-truthful and strict-proper.

In the other 70 worlds:

- OA-mechanism not strong-truthful or proper.
- 01-mechanism is informed-truthful and proper. It is also strict-proper in 19/70 worlds.
- ABCD-mechanism is strong-truthful (symmetric). It is also strict-proper in 12/70 worlds.
- An incomplete, heuristic search for score matrices yields strong-truthful mechanisms in 49/70 worlds.

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| Introduction
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00000000 | Empirical study (MOOCs) | Conclusion |
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34 of 104 worlds are categorical:

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Review: Our Results

- OA-mechanism (generalizes DG'13) is strong-truthful (and strict-proper) for categorical domains.
- 01-mechanism is informed-truthful (and proper) for general domains. Needs knowledge of sign structure of correlations.
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Introduction	The Model	Analysis 00000000	Empirical study (MOOCs)	Conclusion ○●○
Discussion				

- Is there a proper and strong-truthful (symmetric) mechanism for general domains? Perhaps leveraging two S matrices?
- Can heterogeneity be handled (e.g., "pushing" reports towards categorical)?
- Prior-free design: can we use observed data to design and then apply a score matrix?
- Population learning: does strong- or informed-truthful promote convergence to truthful equilibrium?
- Richer models of effort.
- Experiments and applications.

Introduction

The Model

Analysis

Empirical study (MOOCs)

Conclusion ○○●

Thank you