

# Scoring rules

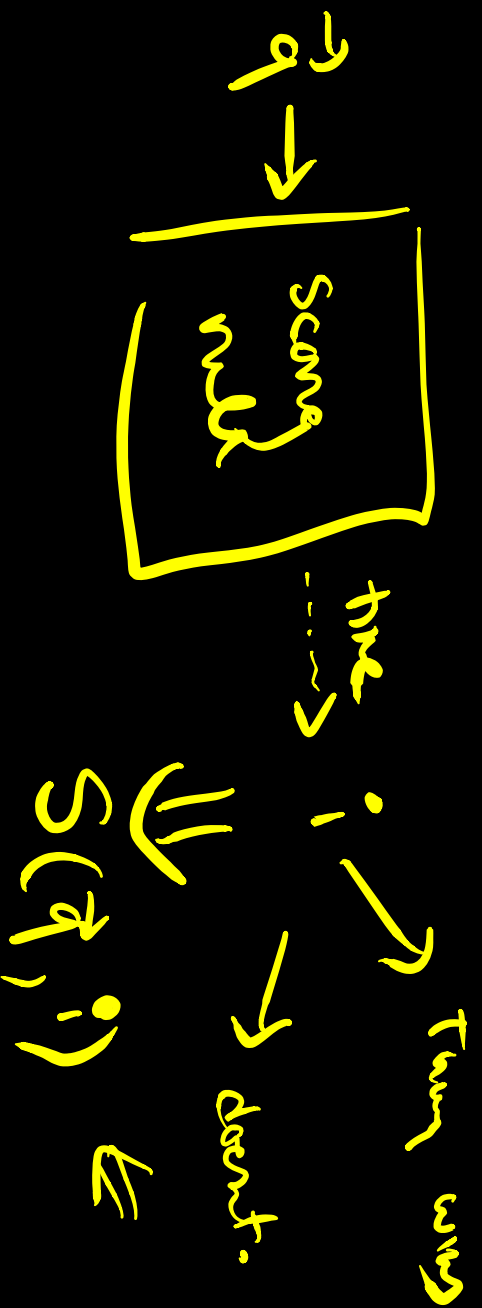
- A different kind of mechanism design problem: **how to elicit a good prediction of an uncertain event?**
  - Weather forecaster: will it rain tomorrow?
  - Political pundit: will a Democrat or Republican win next election?
  - Microsoft employee: will the next version of MS Office ship on time?

# Scoring rules

- A different kind of mechanism design problem: **how to elicit a good prediction of an uncertain event?**
  - Weather forecaster: will it rain tomorrow?
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  - Microsoft employee: will the next version of MS Office ship on time?
- How should we evaluate the quality of a prediction/pay based on the quality of predictions/incentivize the work needed to output the best possible prediction?

# Scoring rules

- $X$  finite set of possible outcomes of uncertain event.
- A **scoring rule** is a real-valued function  $S(\vec{q}, i)$ 
  - $\vec{q}$  is a probability distribution over  $X$  (a prediction)
  - $i$  is some outcome in  $X$  (the realized outcome)



# Model for incentives

$$X = \{s_{un}, r_{un}, s_{env}, s_{env}\}$$
$$p_1, p_2, p_3$$
$$p_1 + p_2 + p_3 = 1$$

- Forecaster has a belief  $p$ , prob distribution over  $X$ .
- Forecaster will choose prediction  $q$  to maximize expected score

forecaster's goal:

choose  $q$  to maximize  $E_{in p}[S(q; i)]$

report  $q \Rightarrow \sum_{i=1}^n p_i S(q; i)$

# Strictly proper scoring rules

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  - $q$  is a probability distribution over  $X$  (a prediction)
  - $i$  is some outcome in  $X$  (the realized outcome)
- A scoring rule is **strictly proper** if, no matter what the true belief  $p$  of the forecaster is, her unique best response is to report truthfully, i.e. to set  $q = p$ .

# Strictly proper scoring rules

- X finite set of possible outcomes of uncertain event.
- A **scoring rule** is a real-valued function  $S(q, i)$ 
  - $q$  is a probability distribution over X (a prediction)
  - $i$  is some outcome in X (the realized outcome)

$$\sum_{i=1}^n p_i S(\vec{q}; i)$$

- A scoring rule is **strictly proper** if, no matter what the true belief  $p$  of the forecaster is, her unique best response is to report truthfully, i.e. to set  $q = p$ .

Example:  $S(\vec{q}; i) = q_i$

value  $(p, 1-p)$

report  $(q, 1-q)$

Exp Payoff =  $p q + (1-p)(1-q)$

Given  $p$  what  $q$  maximizes this?

$p = 0.7$

$0.7q + 0.3(1-q)$

# Quadratic scoring rule

$$S(\vec{q}_i) = q_i - \frac{1}{2} \sum_{j \in X} q_j^2$$

$q_i = 1$  for some  $i$  if  $i$  happens.  $1 - \frac{1}{2} = \frac{1}{2}$

$q_j = 0 \quad \forall j \neq i$  if  $i$  doesn't happen

$-\frac{1}{2}$

$q_i = \frac{1}{2}$  no matter what payoff  $\geq \frac{1}{2}$

$$S(\vec{q}_i) = q_i - \frac{1}{2} \sum_{j \in X} q_j^2$$

QSR is strictly proper

$$E(S_{\text{sum}}) = \sum_i p_i q_i - \frac{1}{2} \sum_{i \in X} p_i \sum_{j \in X} q_j^2$$

is max  
at  $\vec{p} = \vec{q}$

$$\frac{d}{dq_k} E(S_{\text{sum}}) = p_k - \sum_{i \in X} p_i q_k$$

$$a - S + b + \frac{1}{2}$$

$$q_k = \frac{p_k}{\sum_{i \in X} p_i} = p_k$$



# Logarithmic scoring rule

$$S(q_i) = \ln q_i$$

odd  $\ln |X|$

$$|X| = n$$

forecaster can guarantee nonneg exp utility.

$$\vec{p} = \left( \frac{1}{n}, \dots, \frac{1}{n} \right)$$

$$E(\text{score}) = \sum_{i=1}^n p_i \ln\left(\frac{1}{n}\right) + \ln(n) = 0$$

$$-\ln(n)$$

$$q_i = 0$$

$$q_i \geq \epsilon$$



Logarithmic scoring not so strictly  
proper,

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- incentivizing honest feedback
- production markets

# Incentivizing honest feedback

- Example: peer grading, where students grade the assignments of other students.
- How to incentivize accurate grading, without direct verification?

# Model

- n players (graders of an assignment, say in MOOC)
- Player i has a "signal"  $s_i$  → grader's true opinion (quality) homework.
- Each player submits a report  $r_i$  to a mechanism.
- Mechanism pays player  $\pi_i(r_1, \dots, r_n)$

Assume signals drawn from distn.

$n=2$

	$s_2=0$	$s_2=1$
bad $s_1=0$	0.3	0.1
good $s_1=1$	0.1	0.5
	0.4	0.6

$$Pr(s_2=0 | s_1=0) = \frac{3}{4}$$

How to choose payout for  $\Pi_1(\tau^2) \dots \Pi_n(\tau^2)$   
to maximize total reporting?

# Output Agreement *reward agreement.*

- For each player  $i$ 
  - Pick a random player  $j \neq i$
  - Set payoff  $\pi_i$  equal to 1 if they agree, 0 otherwise.

common image



progress meter

message area

# Output Agreement

- For each player  $i$ 
  - Pick a random player  $j \neq i$
  - Set payoff  $\pi_i$  equal to 1 if they agree, 0 otherwise.

Is it a Nash eq to report truthfully

	bad $s_2=0$	good $s_2=1$
bad $s_1=0$	0.3	0.1
good $s_1=1$	0.1	0.5
	0.4	0.6

$s_2 = 0$

$P(s_1=0 | s_2=0) = \frac{3}{4}$

①

	0.1	0.2
1	0.2	0.5



Mechanism has bad NE :

# Peer prediction mechanism

- Suppose the distribution  $D$  over signals is known to mechanism.
- For each player  $i$ 
  - Pick a random player  $j \neq i$
  - Let  $D_j(r_i)$  be the distribution of  $s_j$  conditioned on  $s_i = r_i$
  - Set  $i$ 's payoff  $\pi_i := S(D_j(r_i), r_i)$

Handwritten notes and calculations:

$r_1 = 0$   
 $D_2(s_i=0) = \begin{pmatrix} \frac{3}{4} & \frac{1}{4} \\ 0 & 1 \end{pmatrix}$   
 $S(D_2, 0) \leftarrow$   
 $S(D_2, 1) \leftarrow$   
 $D_2(s_i=1) = \begin{pmatrix} \frac{1}{6} & \frac{5}{6} \end{pmatrix}$

	bad $s_2=0$	good $s_2=1$
bad $s_1=0$	0.3	0.1
good $s_1=1$	0.1	0.5