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Enhancing Crowdsourcing with the Zero-Determinant Game Theory

Dissertation Proposal

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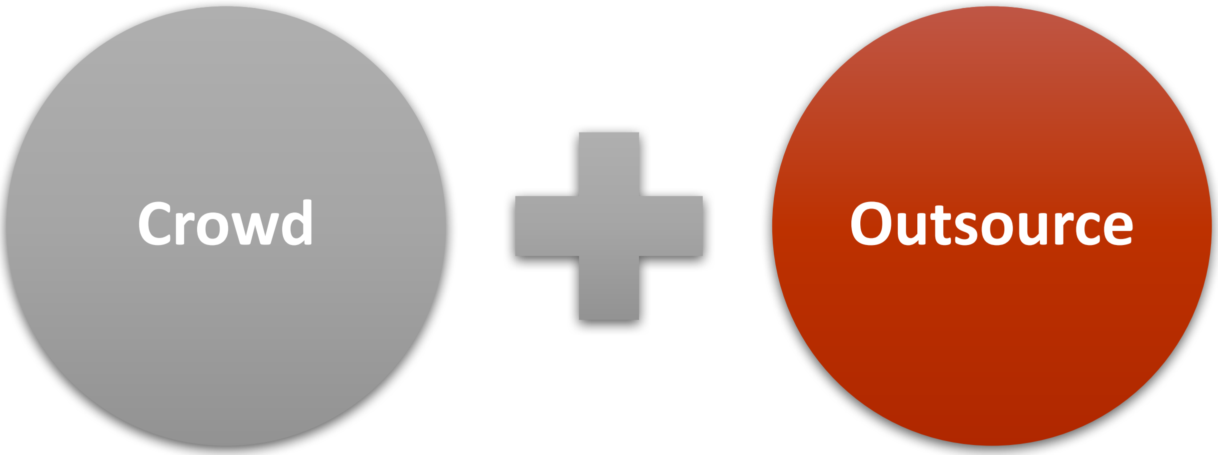
What is crowdsourcing?



Accomplish a complex task via eliciting services from a large group of contributors.

https://collectiveinnovation.com/crowdsourcing-internal-innovation/

Challenges

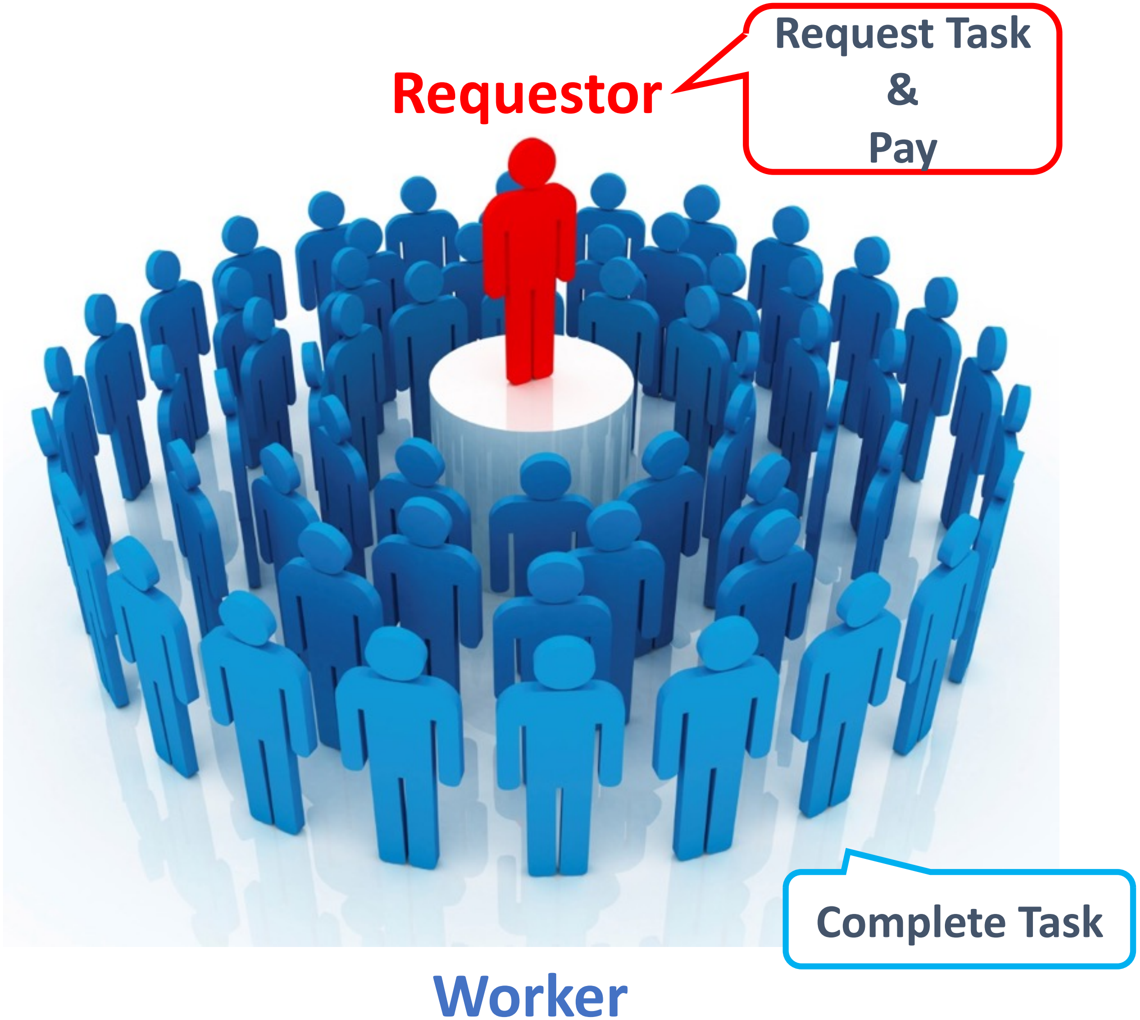
- Skills
- Intents
- Backgrounds

  ...

Overview

- **Eliminating malicious attacks in crowdsourcing**
  - Problem Formulation
  - Strategies for the Worker
  - Intuitive Strategies for the Requestor
  - ZD-Based Algorithm
  - Evaluation
- **Quality control of crowdsourcing**
  - Problem Formulation
  - Extension of the Sequential ZD
  - Sequential ZD based Algorithms and the Evaluation

Problem Formulation



Problem Formulation

Requestor

Worker

Success
- Gather distributed human resources

Openness
- Open to all crowds

Vulnerability
- Malicious attacks

- DARPA Network Challenge, 2009
- DARPA Shredder Challenge, 2011, UCSD

Problem Formulation

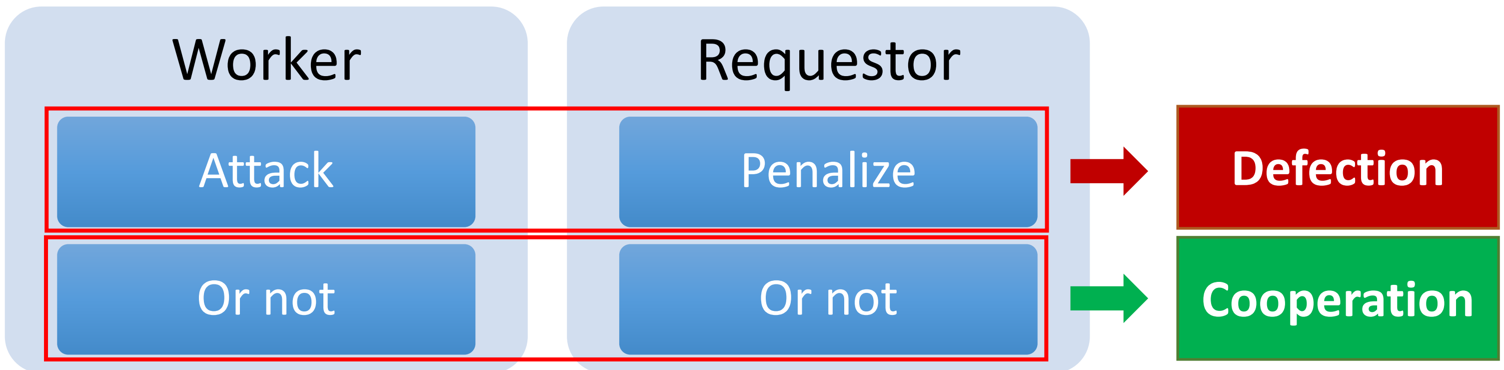
Requestor

Worker

- Game theory
  - The requestor and any one of the worker
  - Two-player simultaneous game
  - Round by round

Problem Formulation

- Actions



- Payoff Matrix

Requestor \ Worker	Cooperation	Defection
Cooperation	$\boldsymbol{R_r, R_w}$	$\boldsymbol{R_r - m, R_w + b}$
Defection	$\boldsymbol{R_r + n, R_w - a}$	$\boldsymbol{R_r - m + n, R_w + b - a}$

Dilemma

Problem Formulation

Challenges

- Whether the requestor should modify the original payoff matrix to eliminate the malicious behavior?
- If it is necessary, how to change the payoff matrix?
- Could the requestor minimize the economic loss resulted from the change of the payoff matrix?

Solutions

- Try local optimization strategy
- Increase short-term payoff with no extra long-term payment
- Guarantee the impartiality

Strategy of the Worker

- Situation

Lack global information

Adaptively search best action

Natural selection, survival of the fittest

- Strategy

Evolutionary Player

- Adjust strategy to maximize payoff regardless of the opponent's strategy and/or payoff
- Two examples
  - E Strategy
  - E' Strategy

Strategy of the Worker

- E Strategy
  - Cooperation probability $q_w^{t+1} = q_w^t \frac{W_c^t}{E_w^t}$

Expected cooperation payoff $W_c^t = p_r^t E(cc) + (1 - p_r^t) E(cd)$

Total expected payoff $E_w^t = q_w^t W_c^t + (1 - q_w^t) W_d^t$

- E' Strategy
  - Cooperation probability $q_w^t = \frac{e^{A_c^t - A_d^t}}{1 + e^{A_c^t - A_d^t}}$

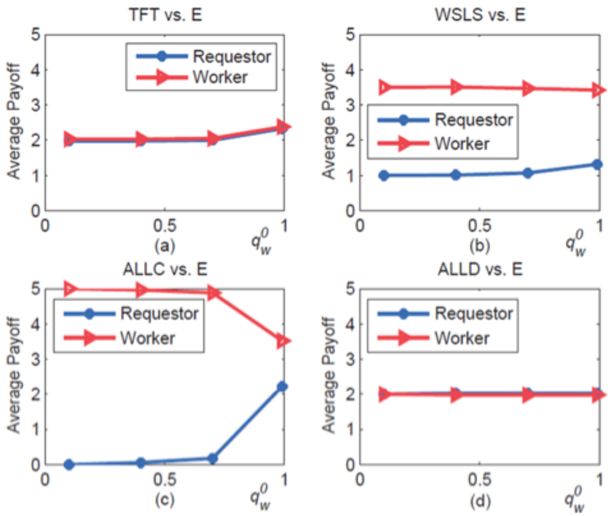
Accumulative expected cooperation payoff $A_c^t = \sum_{\tau=0}^t W_c^\tau$

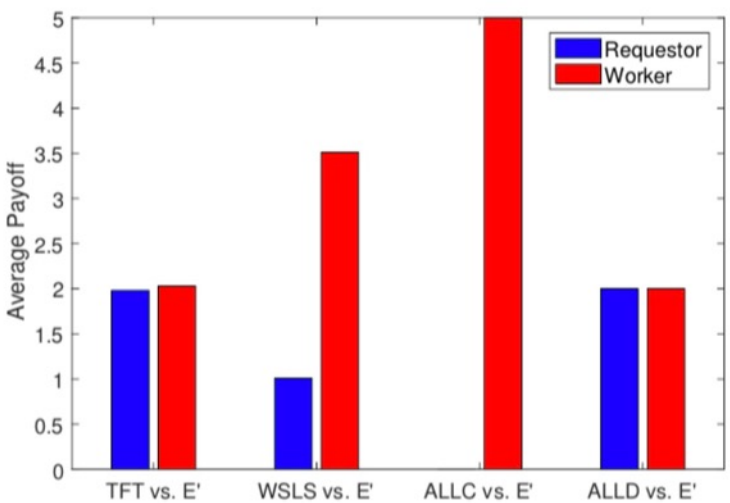
Accumulative expected defection payoff $A_d^t = \sum_{\tau=0}^t W_d^\tau$

Strategy of the Worker

- Reasonability
  - Play with the classic-strategy requestor
    - TFT: tif-for-tat
    - WSLS: win-stay-lose-shift
    - ALLC: all cooperation
    - ALLD: all defection

Theoretical analysis also proved these results.

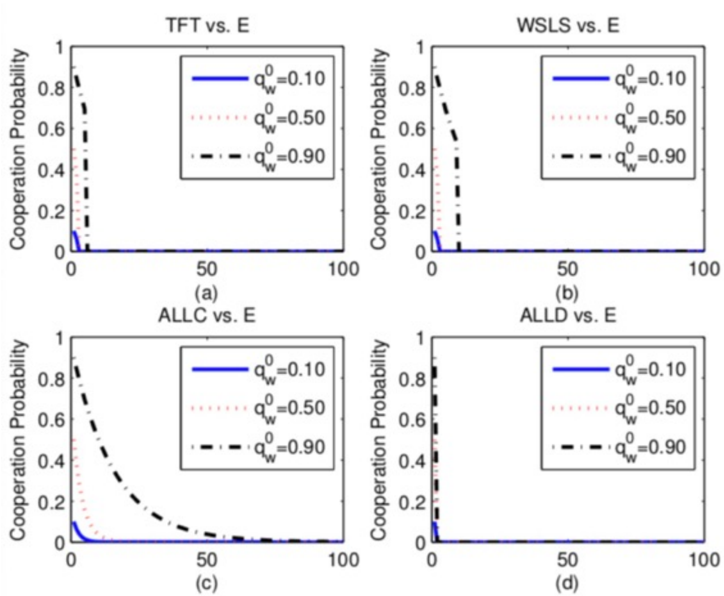


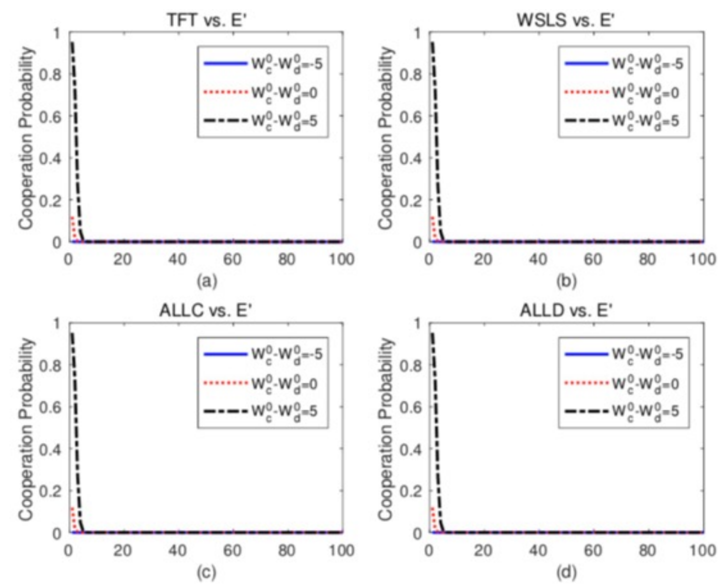


Intuitive Strategies for the Requestor

- What should the requestor do when faced with such a strong opponent?

Classic Strategies

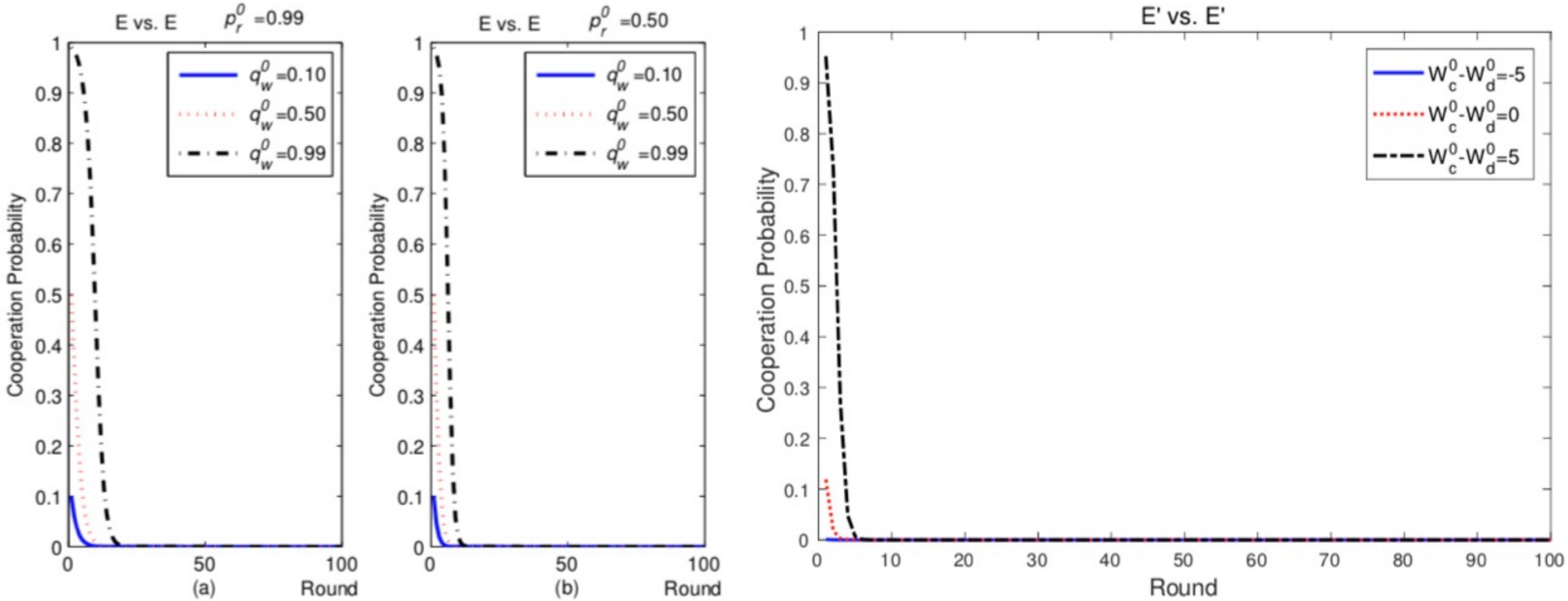




Intuitive Strategies for the Requestor

- What should the requestor do when faced with such a strong opponent?

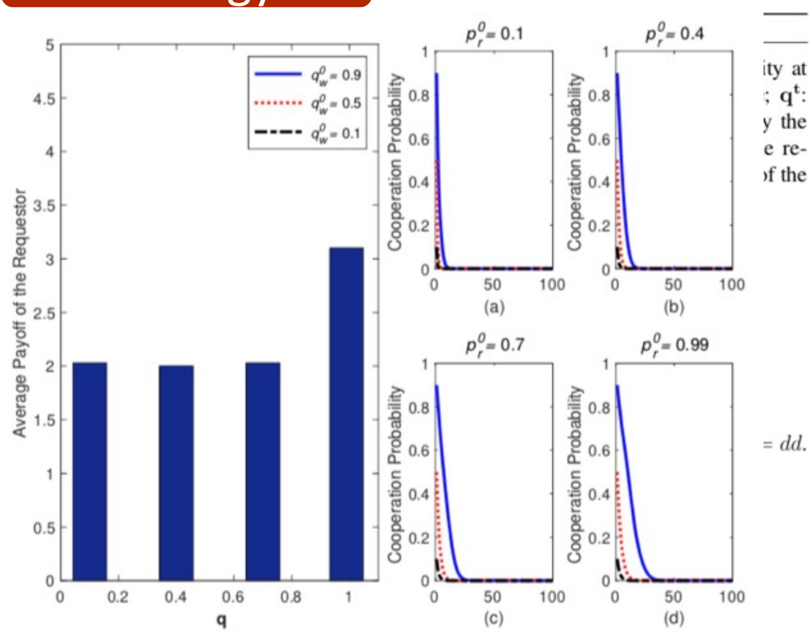
Evolutionary Strategies

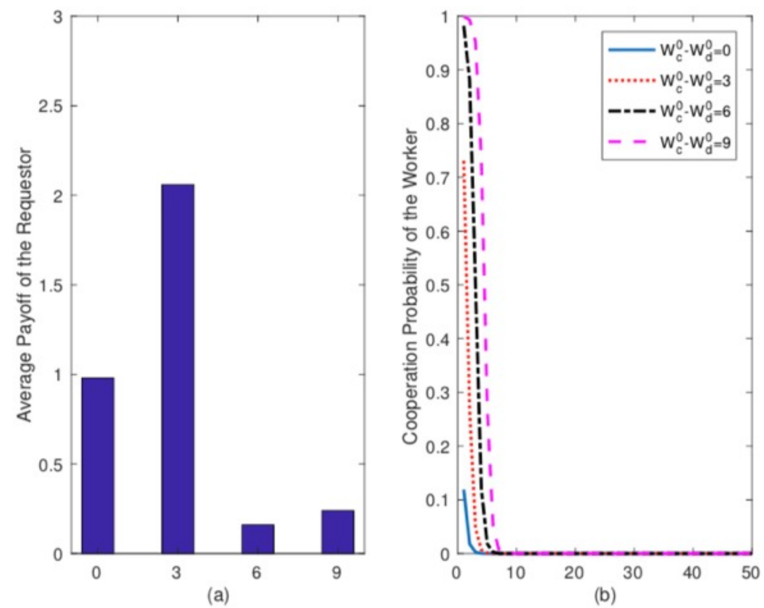


Intuitive Strategies for the Requestor

- What should the requestor do when faced with such a strong opponent?

Local Optimization Strategy





Intuitive Strategies for the Requestor

- Failure analysis
  - E strategy

    $$W_c^t \leq E_w^t \text{ for } p_r^t, q_w^t \in [0,1]$$

    $$\lim_{t\to\infty} q_w^{t+1} = q_w^t \frac{W_c^t}{E_w^t} = 0$$

  - E' strategy

    $$A_c^t - A_d^t \downarrow$$

    $$\lim_{t\to\infty} q_w^t = \frac{e^{A_c^t - A_d^t}}{1+e^{A_c^t - A_d^t}} = 0$$

- Key factor

Payoff Matrix $\rightarrow$ Cooperation Probability

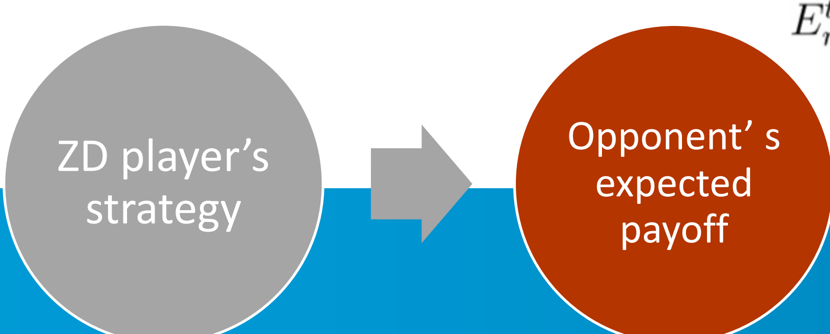
ZD-Based Algorithm

- Aim
  - Elicits the worker's cooperation by increasing its short-term payoff but no any extra long-term payment
- Zero-determinant strategy
  - Proposed by Press and Dyson (2012, PNAS)
  - Set strategy satisfying required condition, we have

$$\forall t,\ \alpha E_r^t + \beta E_w^t + \gamma = 0$$

    - Pinning strategy $\alpha = 0,\ E_w^t = -\frac{\gamma}{\beta}$
    - Extortion strategy $\alpha = \phi,\ \beta = -\phi\chi,\ \gamma = \phi(\chi(R_w + b - a) - (R_r - m + n)),$

$$E_r^t - (R_r - m + n) = \chi(E_w^t - (R_w + b - a)),\ \chi \geq 1$$



ZD-Based Algorithm

- Mixed strategy

Requestor → $\mathbf{p}^t = (p_1^t, p_2^t, p_3^t, p_4^t)$, $rw = (cc, cd, dc, dd)$

Worker → $\mathbf{q}^t = (q_1^t, q_2^t, q_3^t, q_4^t)$, $wr = (cc, cd, dc, dd)$

- Expected payoff $E_r^t = \dfrac{D(\mathbf{p}^t, \mathbf{q}^t, \mathbf{S}_r)}{D(\mathbf{p}^t, \mathbf{q}^t, \mathbf{1})}, E_w^t = \dfrac{D(\mathbf{p}^t, \mathbf{q}^t, \mathbf{S}_w)}{D(\mathbf{p}^t, \mathbf{q}^t, \mathbf{1})}$
- ZD strategy $\widetilde{\mathbf{p}}^t = (-1 + p_1^t, -1 + p_2^t, p_3^t, p_4^t) = \beta \mathbf{S}_w + \gamma \mathbf{1}$

or $\phi[(\mathbf{S}_r - (R_r - m + n)) - \chi(\mathbf{S}_w - (R_w + b - a))]$

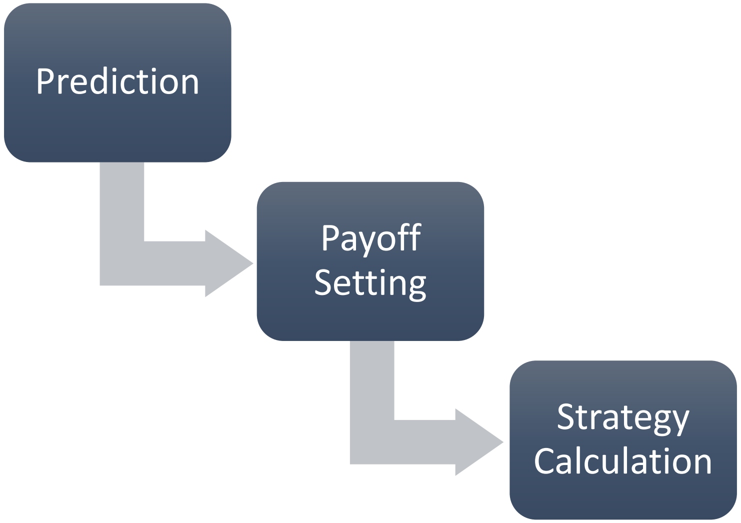
Requestor's strategy → Worker's expected payoff

ZD-Based Algorithm

Algorithm 2 Reward-Penalty Expected Payoff Algorithm based on ZD Strategies

Require: $\mathbf{p}^t$: the requestor's strategy at round t and its initial value is the one used in the last round of the preparatory stage; $\mathbf{P_s} = (P_{cc}, P_{cd}, P_{dc}, P_{dd})$: the state transition probability of the worker, and its initial value is statistically calculated by the data collected in the preparatory stage; N: the total number of rounds.

Initialize(E_w^0)
for $t = 1$ to N **do**
    if The worker's previous move is c **then**
        if $P_{cc} > P_{cd}$ **then**
            Calculate $\mathbf{p}^t$ which makes
            $E_w^t \leftarrow E_w^{t-1} + (max - E_w^{t-1})/2$
        else ▷ $P_{cc} \leq P_{cd}$.
            Calculate $\mathbf{p}^t$ which makes
            $E_w^t \leftarrow E_w^{t-1} - (E_w^{t-1} - min)/2$
        end if
    else ▷ The worker's previous move is d.
        if $P_{dc} > P_{dd}$ **then**
            Calculate $\mathbf{p}^t$ which makes
            $E_w^t \leftarrow E_w^{t-1} + (max - E_w^{t-1})/2$
        else ▷ $P_{dc} \leq P_{dd}$.
            Calculate $\mathbf{p}^t$ which makes
            $E_w^t \leftarrow E_w^{t-1} - (E_w^{t-1} - min)/2$
        end if
    end if
    if The current round terminates **then**
        Update $\mathbf{P_s}$
    end if
end for

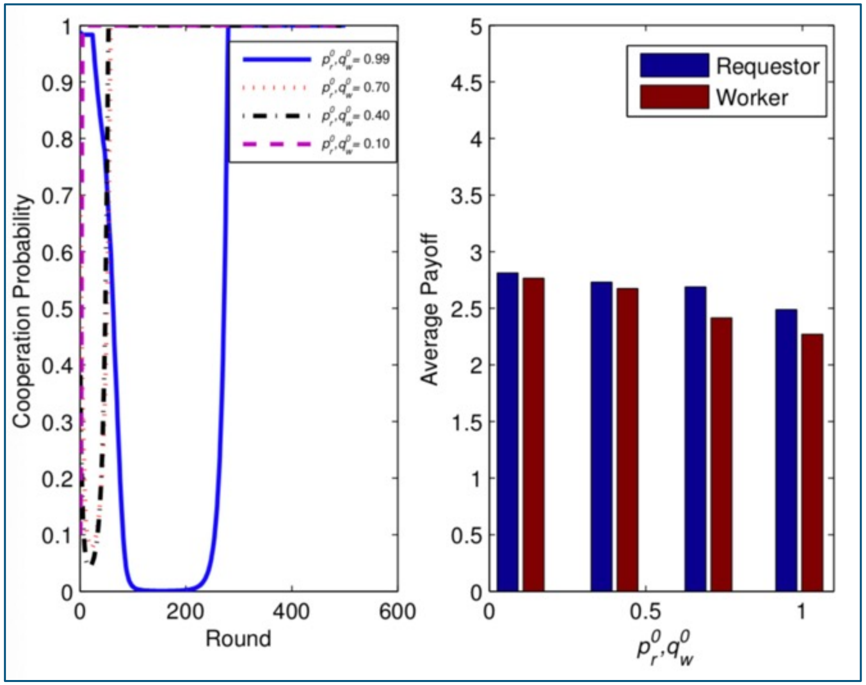


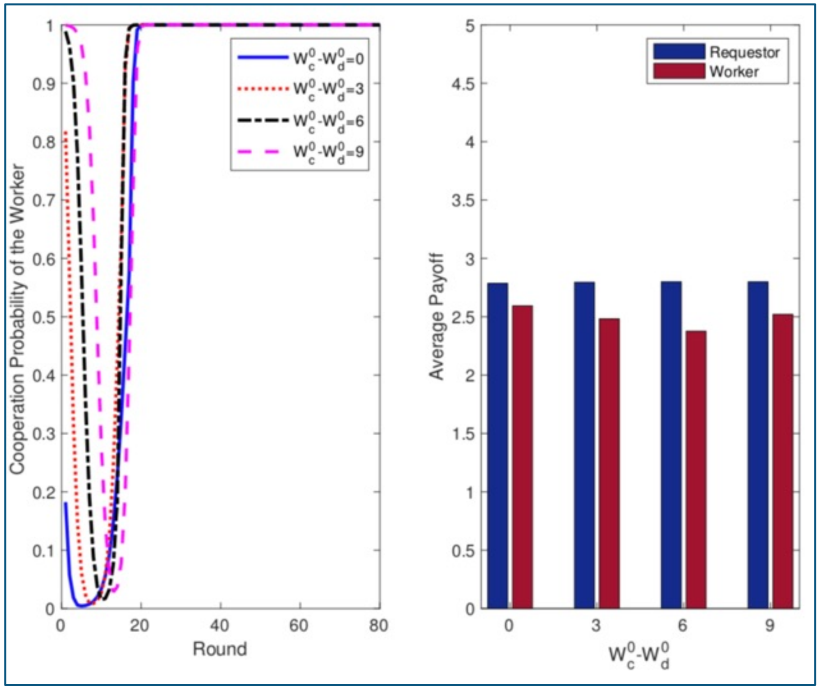
Last Round: *c*
- Predicted to be *c* - E_w^t ↑
- Predicted to be d - E_w^t ↓

Last Round: *d*
- Predicted to be *c* - E_w^t ↑
- Predicted to be d - E_w^t ↓

Evaluation

Theoretically proved





Effectiveness

Fairness

Liveliness

Overview

- **Eliminating malicious attacks in crowdsourcing**
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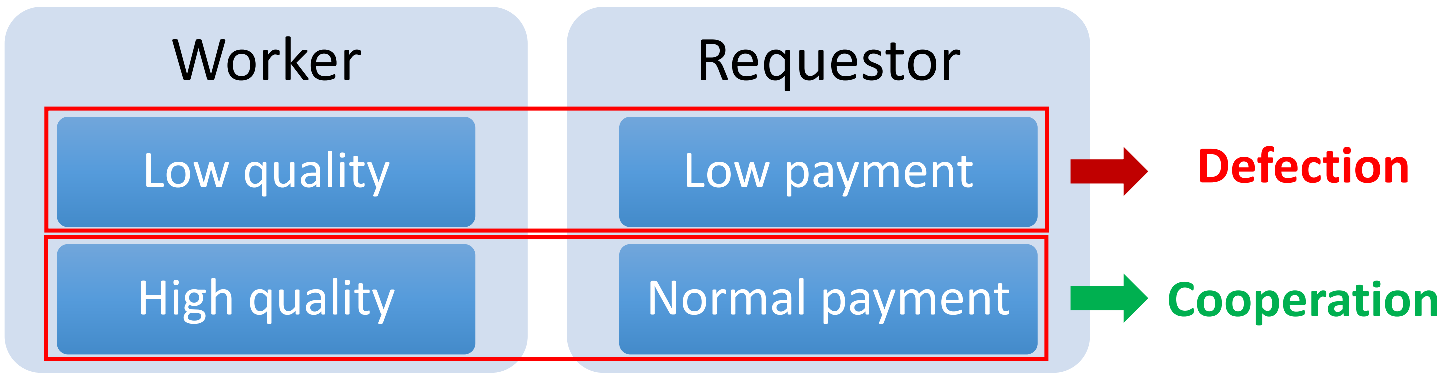
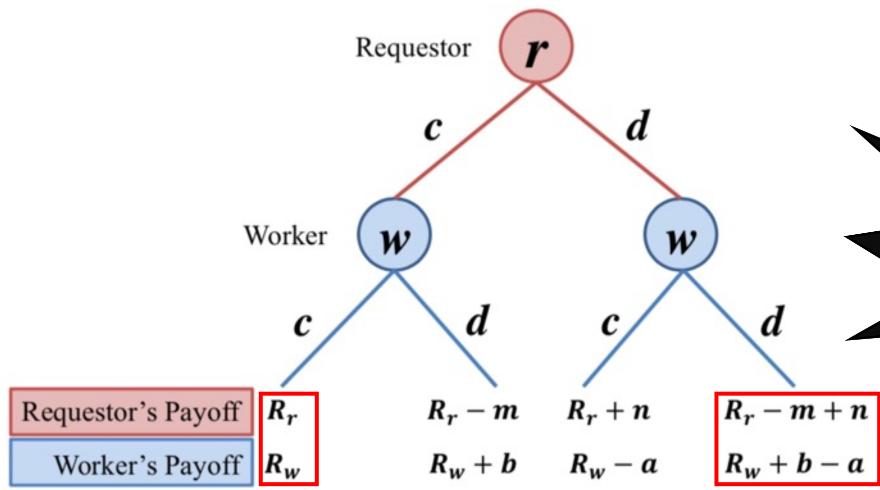
Problem Formulation

Problem Formulation

- Actions



- Game Tree



Sequential Dilemma

Problem Formulation

- Actions

$\{c, d\} \times \{c, d\}$

$[l_r, h_r] \times [l_w, h_w]$

Utility Functions

$$w_r(x, y) = A_r \phi(y) - B_r x$$

$$w_w(x, y) = A_w x - B_w \psi(y)$$

Nash Equilibrium

$$(x^*, y^*) = (l_r, l_w)$$

Sequential dilemma still exists!

Extension of the Sequential ZD

- Mixed strategy

Requestor → $\mathbf{p}^t = (p_1^t, p_2^t, p_3^t, p_4^t)$, $xy = (cc, cd, dc, dd)$

Worker → $\mathbf{q}^t = (q_1^t, q_2^t)$, $x = (c, d)$

- Only the requestor can adopt the ZD strategy

$$\begin{bmatrix} p_1^t q_1^t - 1 & p_1^t - 1 & q_1^t - 1 & f_1 \\ p_2^t q_3^t & p_2^t - 1 & q_2^t & f_2 \\ p_3^t q_3^t & p_3^t & q_3^t - 1 & f_3 \\ p_4^t q_4^t & p_4^t & q_4^t & f_4 \end{bmatrix} \Rightarrow \begin{bmatrix} p_1^t q_1^t - 1 & p_1^t - 1 & (1-p_1^t)q_2^t + p_1^t q_1^t - 1 & f_1 \\ p_2^t q_1^t & p_2^t - 1 & (1-p_2^t)q_2^t + p_2^t q_1^t & f_2 \\ p_3^t q_1^t & p_3^t & (1-p_3^t)q_2^t + p_3^t q_1^t - 1 & f_3 \\ p_4^t q_1^t & p_4^t & (1-p_4^t)q_2^t + p_4^t q_1^t & f_4 \end{bmatrix}$$

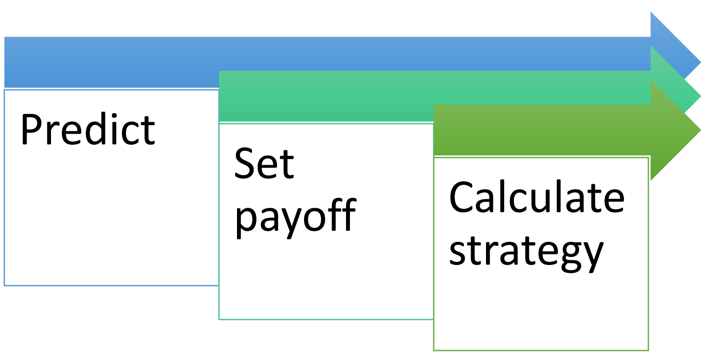
The first mover therefore obtain the advantage.

Sequential ZD based Algorithms

- Binary model

- Evolutionary worker

$$q_w^{t+1} = q_w^t \frac{W_c^t}{\tilde{E}_w^t}$$



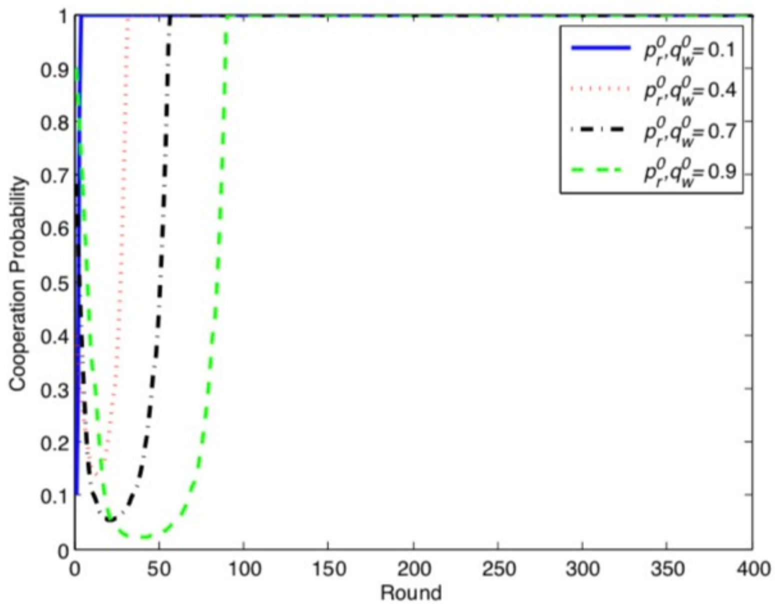
Algorithm 3 Sequential ZD based Incentive Algorithm for the Binary Model

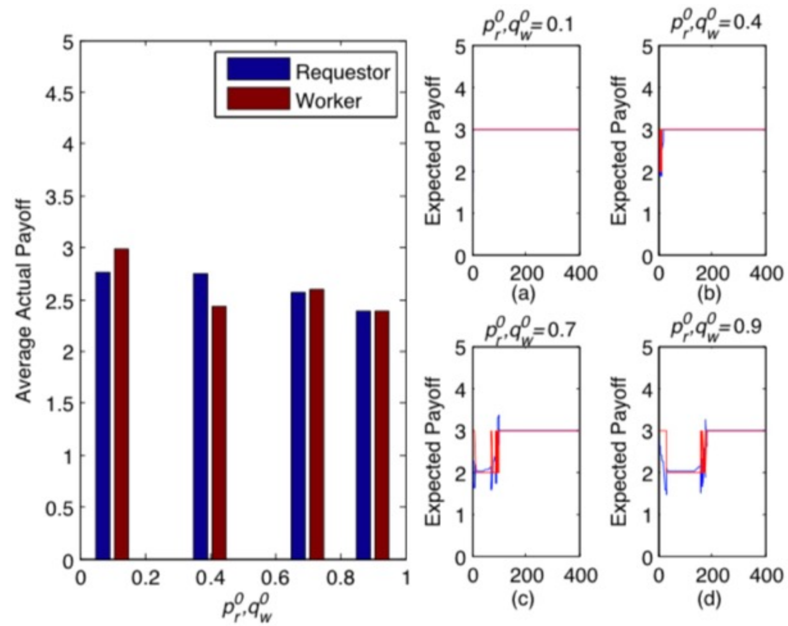
Require: $\mathbf{p}^i = \{p_1^i, p_2^i, p_3^i, p_4^i\}$: the requestor's strategy at round i and its initial values are the ones used in the N_0^{th} round; $\mathbf{P}_s = (P_{cc}, P_{cd}, P_{dc}, P_{dd})$: the state transition probabilities of the worker, and their initial values are calculated statistically through the preparatory N_0 rounds; N: the total number of rounds.

Initialize $(\tilde{E}_w^0)$
for $i = 1$ to N **do**
  if The worker's last move is c **then**
    if $P_{cc} > P_{cd}$ **then**
      Set $\{p_1^i, p_2^i, p_3^i, p_4^i | \frac{(1-p_1^i)(R_w+b-a)+p_4^i R_w}{1-p_1^i+p_4^i} = R_w \wedge 0 \le p_1^i, p_2^i, p_3^i, p_4^i \le 1\}$
      $\tilde{E}_w^i \leftarrow R_w$
    else ▷ $P_{cc} \le P_{cd}$.
      Set $\{p_1^i, p_2^i, p_3^i, p_4^i | \frac{(1-p_1^i)(R_w+b-a)+p_4^i R_w}{1-p_1^i+p_4^i} = R_w+b-a \wedge 0 \le p_1^i, p_2^i, p_3^i, p_4^i \le 1\}$
      $\tilde{E}_w^i \leftarrow R_w + b - a$
    end if
  else ▷ The worker's last move is d.
    if $P_{dc} > P_{dd}$ **then**
      Set $\{p_1^i, p_2^i, p_3^i, p_4^i | \frac{(1-p_1^i)(R_w+b-a)+p_4^i R_w}{1-p_1^i+p_4^i} = R_w \wedge 0 \le p_1^i, p_2^i, p_3^i, p_4^i \le 1\}$
      $\tilde{E}_w^i \leftarrow R_w$
    else ▷ $P_{dc} \le P_{dd}$.
      Set $\{p_1^i, p_2^i, p_3^i, p_4^i | \frac{(1-p_1^i)(R_w+b-a)+p_4^i R_w}{1-p_1^i+p_4^i} = R_w+b-a \wedge 0 \le p_1^i, p_2^i, p_3^i, p_4^i \le 1\}$
      $\tilde{E}_w^i \leftarrow R_w + b - a$
    end if
  end if
  if The current round ends **then**
    Update $\mathbf{P}_s$
  end if
end for

Sequential ZD based Algorithms

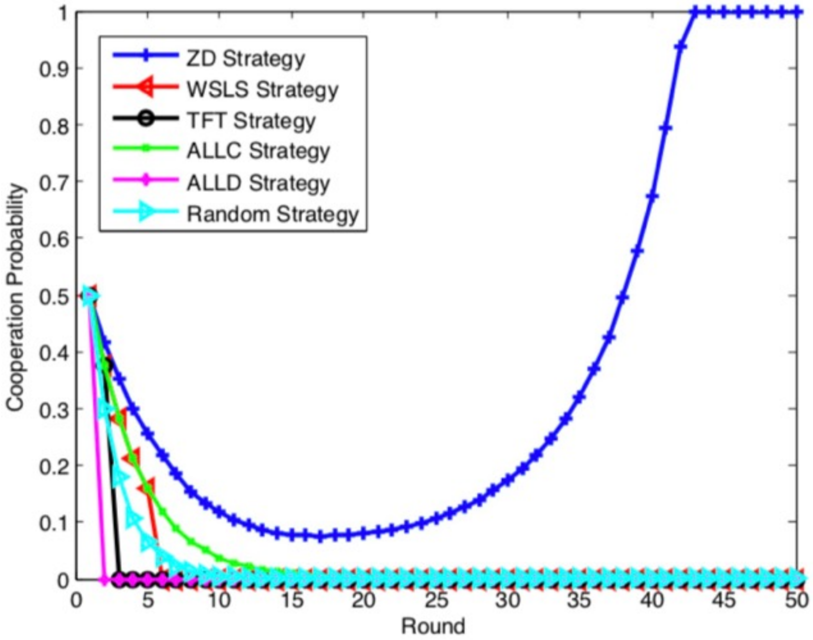
- Binary model

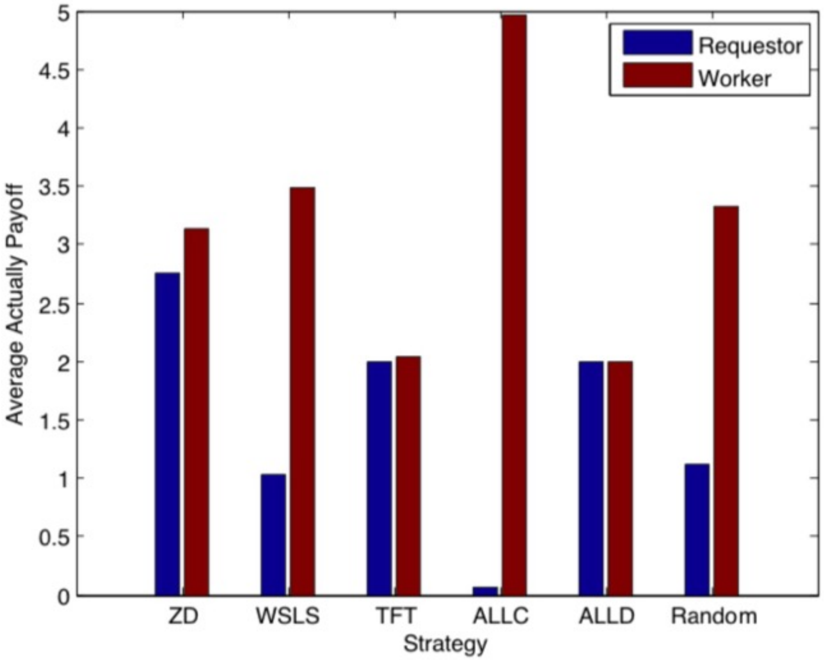




Sequential ZD based Algorithms

- Binary model





Sequential ZD based Algorithms

- Continuous model

Algorithm 4 Sequential ZD Strategy based Incentive Algorithm for the Continuous Model

Require: $p^t(x|x_{-1}, y_{-1})$: the requestor's strategy and its initial value is the one used in the N_0^{th} round; $\mathbf{P}_s^c = \{P_{ij}^c\}_{\eta\times\eta}$: the state transition probability of the worker, and its initial value is calculated statistically through the preparatory N_0 rounds; N: the total number of rounds for algorithm termination.

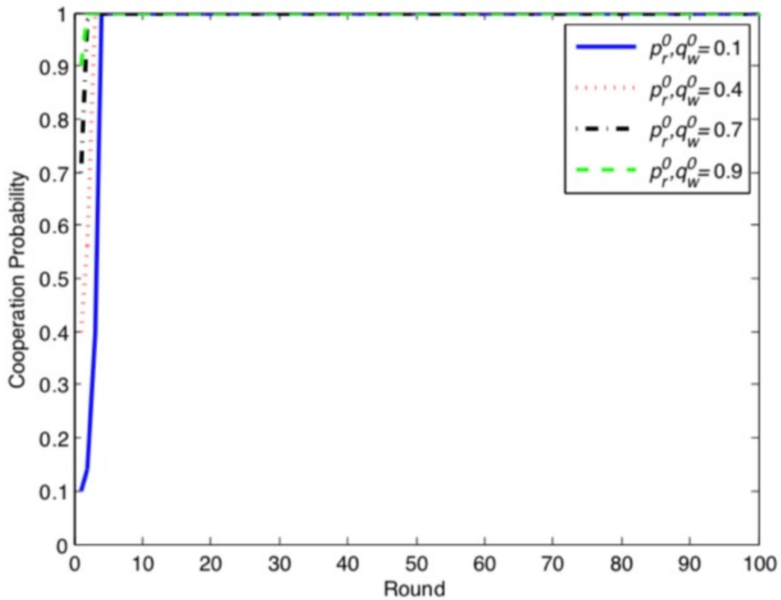
Initialize(E_w^0)
for $i = 1$ to N **do**
    if $y^{i-1} \in [l_w + (\kappa - 1)\delta, l_w + \kappa\delta]$ **then**
        if $P_{\kappa-\eta}^c \geq P_{\kappa-j}^c, \forall j \in \{1, w, \cdots, \eta\}$ **then**
            Set $p^i(x|x_{-1}, y_{-1})$ to let
            $E_w^i \leftarrow \max(E_w^t)$
        else $\triangleright\ P_{\kappa-\eta}^c < P_{\kappa-j}^c$.
            Set $p^i(x|x_{-1}, y_{-1})$ to let
            $E_w^i \leftarrow \min(E_w^t)$
        end if
    end if
    if The current round ends **then**
        Update $\mathbf{P}_s^c$
    end if
end for

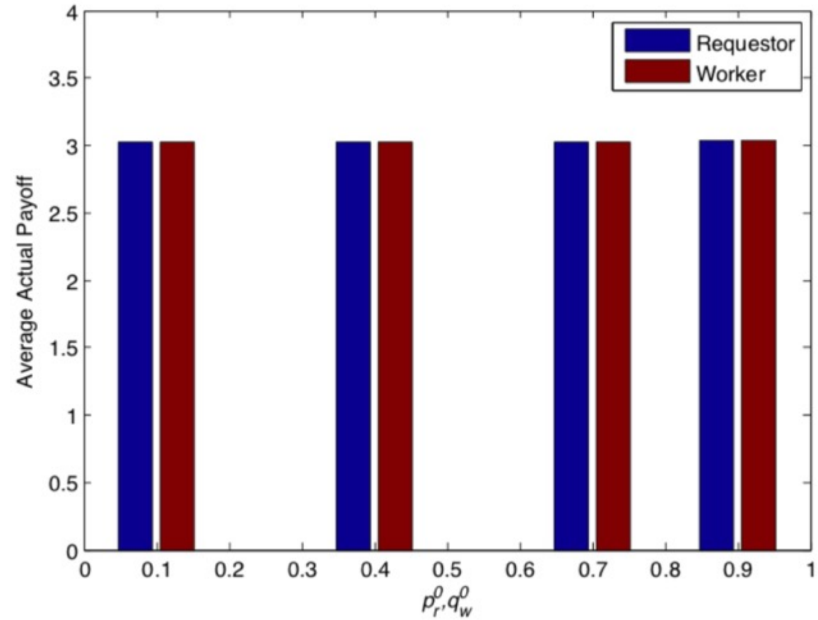
- Evolutionary worker

$$f_h^{t+1} = f_h^t \frac{W_h^t}{E_w^t}$$

Sequential ZD based Algorithms

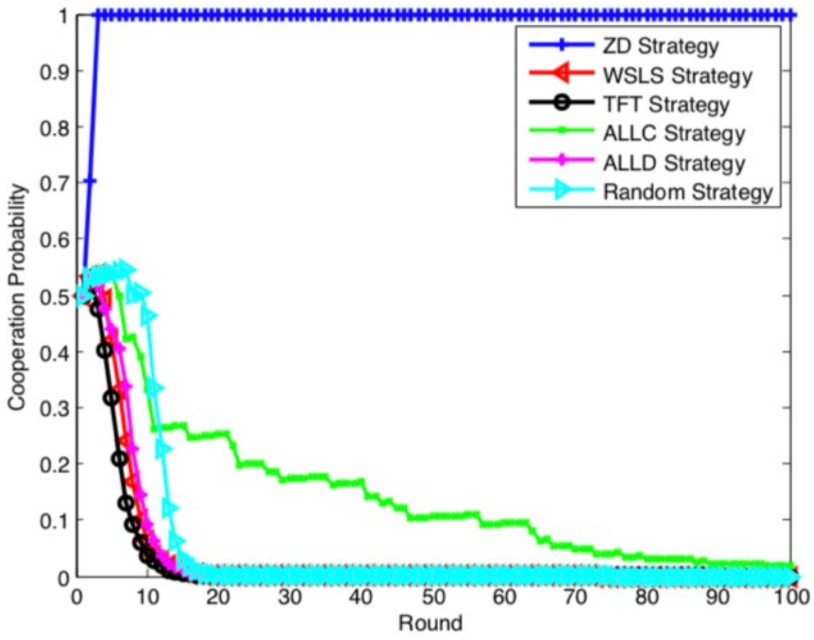
- Continuous model

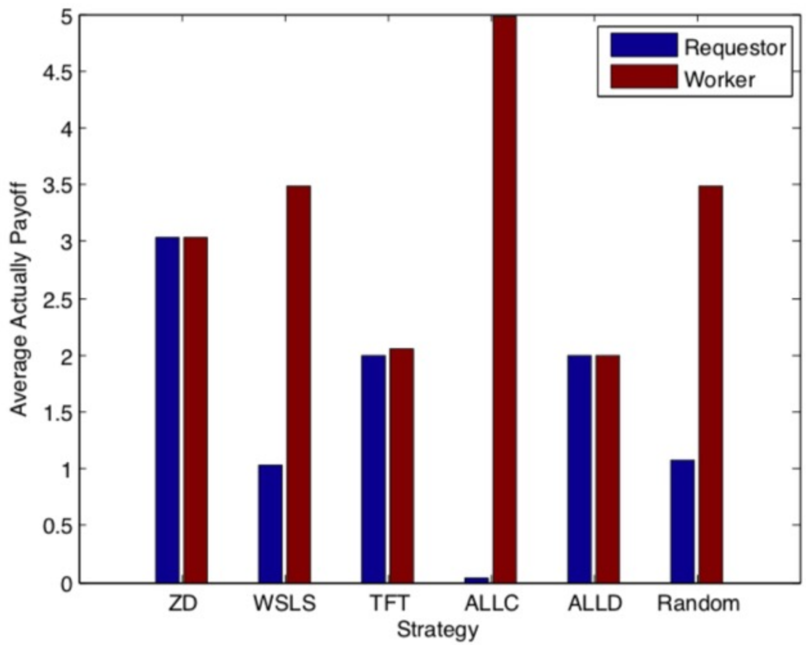




Sequential ZD based Algorithms

- Continuous model





Related Papers

- **Qin Hu**, Shengling Wang*, Peizi Ma, Xiuzhen Cheng, Weifeng Lv, Rongfang Bie. Quality Control in Crowdsourcing Using Sequential Zero-Determinant Strategies, IEEE Transactions on Knowledge and Data Engineering, submitted.
- **Qin Hu**, Shengling Wang*, Xiuzhen Cheng, Liran Ma, Rongfang Bie. Solving the Crowdsourcing Dilemma Using the Zero-Determinant Strategies, IEEE Transactions on Information Forensics and Security, submitted.
- **Qin Hu**, Shengling Wang*, Chunqiang Hu, Jianhui Huang, Wei Li, Xiuzhen Cheng. Messages in a Concealed Bottle: Achieving Query Content Privacy with Accurate Location-Based Services, *IEEE Transactions on Vehicular Technology,* 2018, 67 (8), 7698-7711.
- **Qin Hu**, Shengling Wang*, Rongfang Bie, Xiuzhen Cheng. Social Welfare Control in Mobile Crowdsensing Using Zero-Determinant Strategy, *Sensors*, 2017, 17(5): 1012.
- **Qin Hu**, Shengling Wang*, Liran Ma, Rongfang Bie, Xiuzhen Cheng. Anti-Malicious Crowdsourcing Using the Zero-Determinant Strategy, Distributed Computing Systems (ICDCS), 2017 IEEE 37th International Conference on. IEEE, 2017: 1137-1146.

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Thank you!