



Verifiable Crowd Computing

Coping with Bounded Rationality

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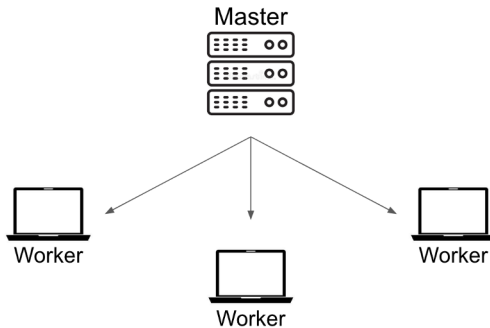
Abstract

- Verifiable crowd computing
- Repeated game framework
- Master-Worker mechanism
- Perfect vs. bounded rationality
- Rewards and punishment
- Terminal payoff



Introduction

- Outsourcing computation to lower computing costs, both financially and computationally.
- Practical examples: SETI@home, Foldit, Mechanical Turk, etc.



The most prominent problem

How can a client ensure that the computational tasks have been performed correctly by the untrusted workers?

Master-Worker (MW) Model

Proposed Model

Shortcomings of existing models^[1-4]:

- Either honest or malicious workers.
- Perfectly rational players assumed.
- Equilibrium deviators jeopardize correctness guarantees.
- Not practical in real world.

We address above shortcomings by augmenting the repeated game based MW model of Fernandez Anta et al. ^[5]

1. Christoforou, E., Fernández Anta, A., Georgiou, C., Mosteiro, M.A.: Algorithmic mechanisms for Internet supercomputing under unreliable communication. In: Proc. of the 10th IEEE International Symposium on Network Computing and Applications. pp. 275–280 (2011).
2. Fernández Anta, A., Georgiou, C., Mosteiro, M.A.: Designing mechanisms for reliable Internet-based computing. In: Proc. of the 7th IEEE International Symposium on Network Computing and Applications. pp. 315–324 (2008).
3. Fernández Anta, A., Georgiou, C., Mosteiro, M.A., Pareja, D.: Algorithmic mechanisms for reliable crowdsourcing computation under collusion. Public Library of Science One 10(3) (2015).
4. Heien, E., Anderson, D., Hagihara, K.: Computing low latency batches with unreliable workers in volunteer computing environments. Journal of Grid Computing 7, 501–518 (2009).
5. FernándezAnta,A.,Georgiou,C.,Mosteiro,M.A.,Pareja,D.:Multi-round master-worker computing: a repeated game approach. In: Proc. of the IEEE 35th Symposium on Reliable Distributed Systems. pp. 31–40. IEEE (2016).



Proposed Model

Finitely repeated game based Master-Worker Model

Master


- Sets system parameters, such as reward threshold, probability of computing.
- Assigns computing tasks.
- Chooses whether to verify results or accepts the majority.
- Rewards workers.

Workers

Followers:

- Follow prescribed equilibrium.
- Look for deviation and impose peer punishment if needed.

Deviators:

- Have bounded rationality.
 - Behave as rational followers after peer punishment.
- 

Proposed Model

Master

Probability of verification: The probability of the master verifies the results.

Acceptance of results: The master either accepts the majority or verifies the results.

Fine: The workers who provide false results are fined only after the masters' verification.

Rewards: The workers receive rewards after the acceptance of results.

Reward threshold: The maximum number of workers can be rewarded in each round, set by the master.

Terminal payments: Incentivize followers for peer punishment.

Workers

Probability of computing: The probability of the worker will compute in a round.

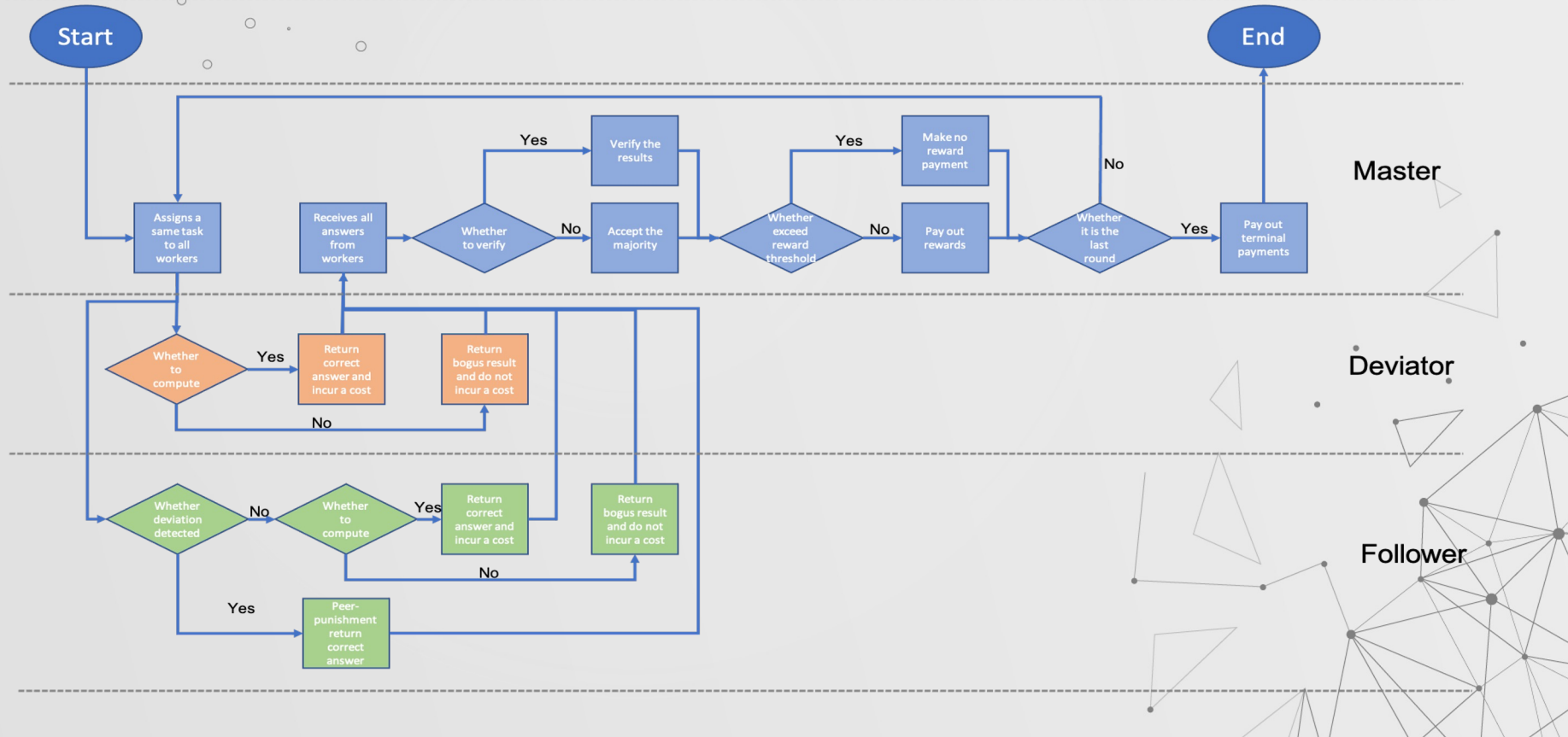
Computing cost: The cost incurred by the worker if it choose to compute.

Deviation detection: Detection of deviation before imposing peer-punishment.

Peer-punishment: Once deviation detected, followers switch to min-max strategy that yields the lowest payoff that followers can force upon a deviator. The terminal payments compensate for followers' short-term utility loss.

Peer-punishment period: The number of rounds that peer-punishment needs to counter any extra utility that may be obtained by the deviators.

Algorithmic Mechanism



Analysis

A pareto-efficient repeated game equilibrium

For any enforceable payoff profile, that is, any payoff profile where the expected utility for each worker is **at least the minmax payoff**, there exists a Nash equilibrium payoff profile that all workers will follow due to long-term rationality.

We identify a strategy profile that **maximizes** the workers expected utility by finding **bounds for the probability of computing** such that all workers can use a same probability for the mixed strategy equilibrium.

Analysis

Deviation-detection method

- Using Chernoff bounds for bounding the number of correct answers that should be obtained with high probability in rounds.
- Can be strong deviations occur over a few rounds or slight deviations occur over many rounds, or both.
- Workers can keep track of the number of correct answers sent by the master, and use the corresponding count to compute the total number of correct answers.

Analysis

Peer punishment and terminal payoffs

The minmax strategy can be imposed by followers:

- The choice of probability of computing.
- The probability of computing is 1.

The length of punishment phase:

- The total extra utility gained by the deviators.
- The difference between the expected utility of any worker and utility under the minmax strategy.

Terminal payoffs:

- The amount the master pays followers at the end to compensate them for their loss of utility while using the minmax strategy.



Analysis

Mechanism Properties

1. Show bounds on the mixed strategy equilibrium, a probability of computing, in which workers maximize their expected utility.
2. Analyze how deviations can be detected with high probability, using Chernoff Bounds.
3. Provide bounds on the length of the peer-punishment phase
4. Provide bounds on the terminal payoffs that compensate followers for their loss
5. Show that the master can achieve the expected correctness.



Simulation and Results

We compare the performance of the proposed approach (FRG) with

- Evolutionary dynamics mechanism (ED)^[1]
 - A reinforcement learning based approach
 - Workers update their probability of computing in each round based on the previous round's probability
 - All workers comply with the mechanism
- Infinitely repeated games mechanism (IRG)^[2]
 - All rational workers follow the equilibrium because of the threat of punishment
 - Deviation is readily detected after one round (optimal detection)
 - Deviators become followers after one round of punishment
 - For comparable results, we assume workers do not know the interaction with the master is finite

1. Christoforou, E., Fernández Anta, A., Georgiou, C., Mosteiro, M.A., Sánchez, A.: Applying the dynamics of evolution to achieve reliability in master-worker computing. *Concurrency and Computation: Practice and Experience* 25(17), 2363–2380 (2013)

2. FernándezAnta,A.,Georgiou,C.,Mosteiro,M.A.,Pareja,D.:Multi-round master-worker computing: a repeated game approach. In: *Proc. of the IEEE 35th Symposium on Reliable Distributed Systems*, pp. 31–40. IEEE (2016)

Simulation and Results

Universal parameters

- 40% of workers are deviators
- Deviations occur only once in all three mechanisms
- Number of workers: 9, 99 and 999
- Number of rounds: [20, 1000]
- Reward and fine: 10
- Computing cost: 2
- Master's probability of verification: fine / computing cost = 0.2

FRG parameters

- Followers' probability of computing at equilibrium: 0.55
- Deviators' probability of computing: 0.9

ED parameters

- Workers aspiration for profit: 0.1
- Learning rate: 0.01
- Master tolerance to error: 0.5
- Initial followers' probability of computing: 0.5
- Initial deviators' probability of computing: 0.9

IRG parameters


- Cost of verification: 0
- Profit from being correct: 0
- Cost of being wrong: 0
- Cost of accepting an answer: 10
- Followers' probability of computing at equilibrium: 0.9
- Deviators' probability of computing: 0.5
- Most favorable choice for IRG



Simulation and Results

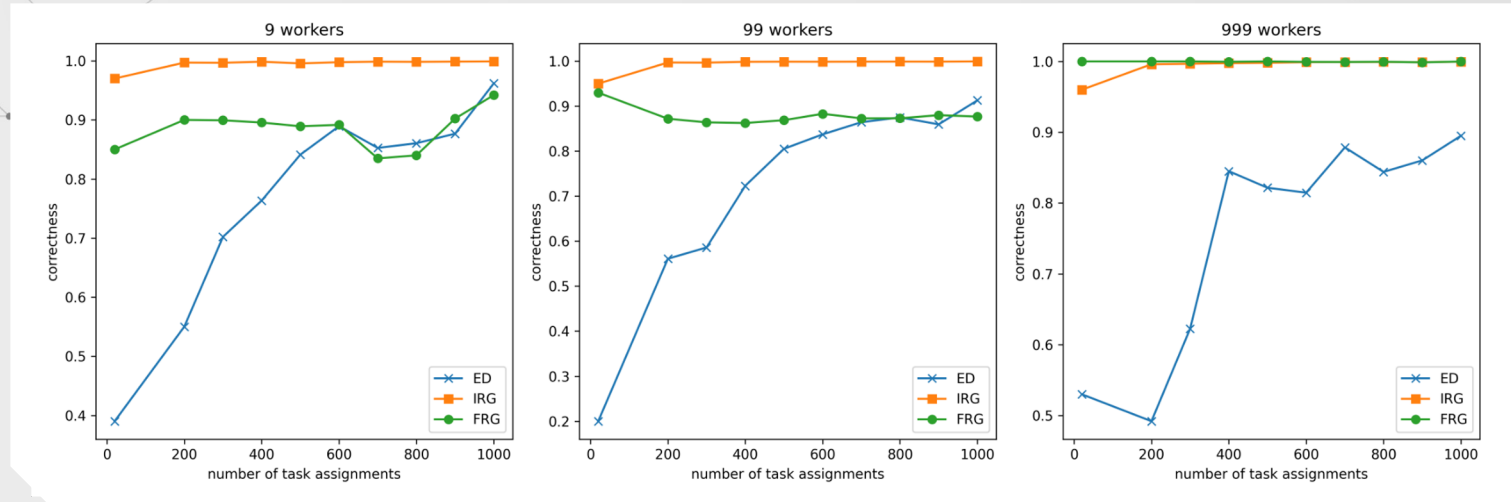
Results are the average of 10 executions of each mechanism.

Two performance measurement:

- **Correctness**, the number of correct answers obtained by the master divided by the total number of tasks.
 - **Master cost**, the total cost incurred by the master.
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Simulation and Results

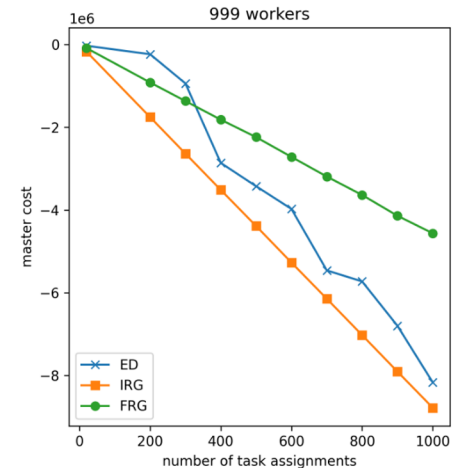
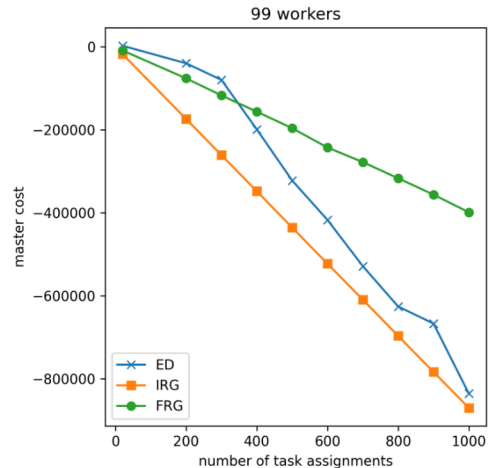
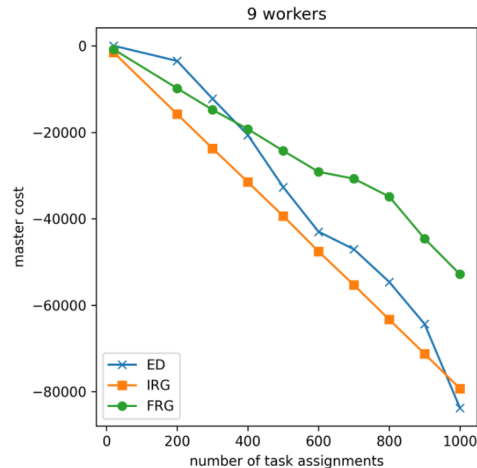
Correctness



- For less than 100 workers and any number of tasks up to 400, FRG performs better than ED.
- The master can configure the number of tasks since it is a design choice in the mechanism.
- Results for IRG are optimistic since we assumed all workers are unaware of the number of rounds.

Simulation and Results

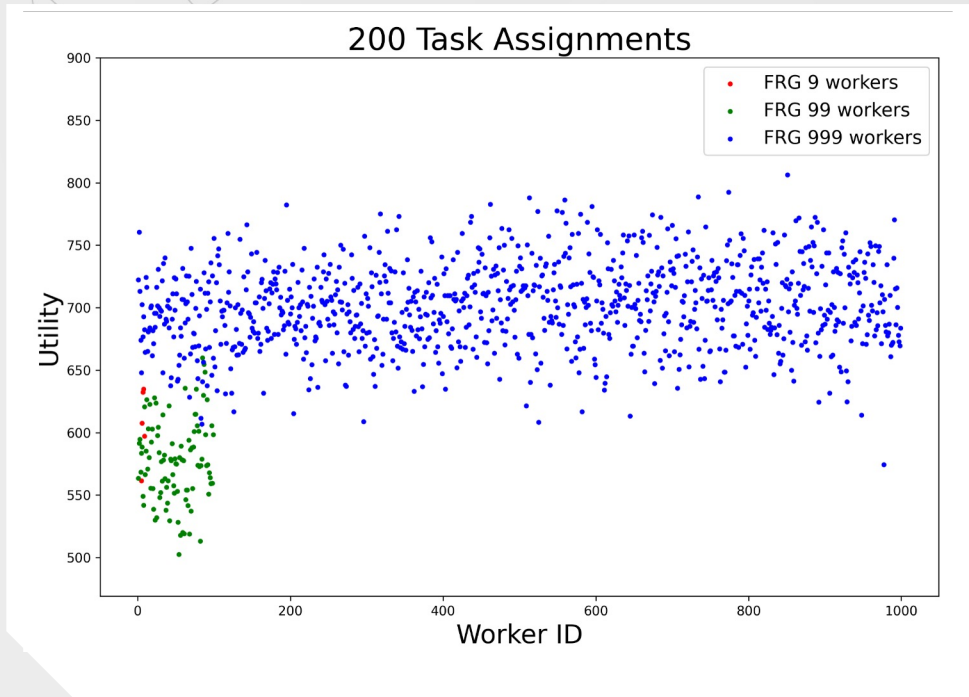
Master Cost



- For any number of tasks up to 400, FRG has similar master cost but achieved better correctness than ED.
- IRG has the largest master cost among three mechanisms.
- FRG achieves comparable, if not better, results in both correctness and master cost when the number of workers is large.

Simulation and Results

Workers' Utility



- Positive expected utility for each worker.
- Confirms the feasibility of the mechanism.
- Simulation for 200 task assignments, other values gave similar results.

Main Contributions

Modeling deviators

- Generalizes the repeated-game MW model.
- Allows for the presence of bounded-rational workers or deviators.
- Bridges the gap between game theory and rational behavior in practice.
- Models intentional deviations as opposed to accidental deviations.

Terminal payments

- Implements terminal payments constructively.
- Incentivizes workers to impose peer punishment.



Main Contributions

Verifiable MW computing in the presence of deviators

- Provides a robust MW mechanism against deviating workers.
- Achieves correctness guarantees in a weaker behavioral model_[1].

Simulation results

- Experimentally, the performance is better than the previous models.
- Correctness and master's cost.

Future Work

- Richer model of worker behaviors, e.g. deviating more than once.
- Introduce malicious players.
- Consider peer-punishment only, i.e. removing master's fine.
- Connections to Computational Complexity Theory, e.g. prover-verifier model.





THANKS

Does anyone have any questions?

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