MACRO: Incentivizing Multi-leader Game-based Pareto-efficiency Crowdsourcing for Video Analytics

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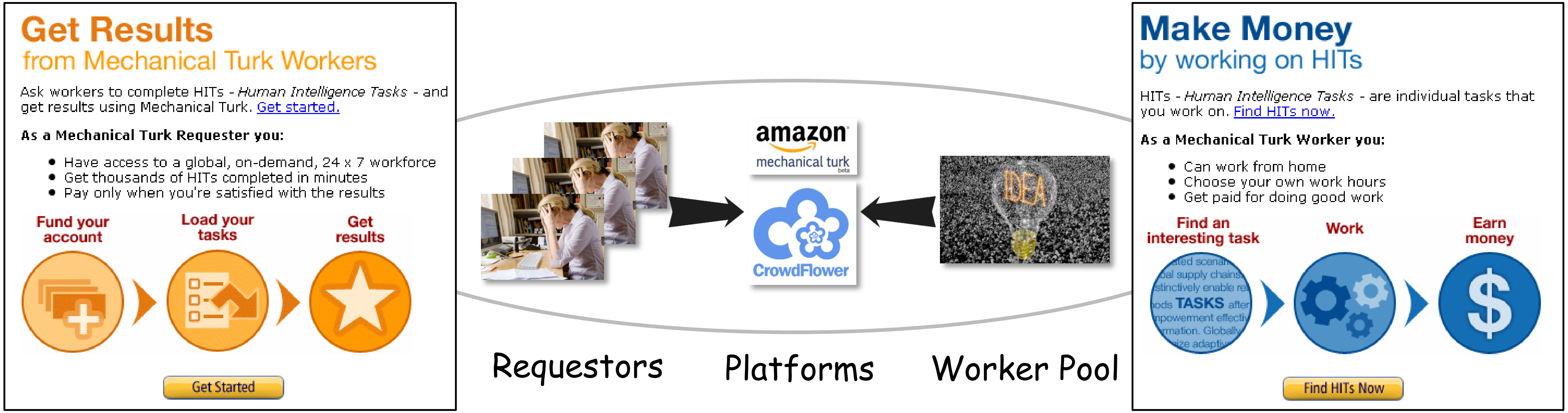
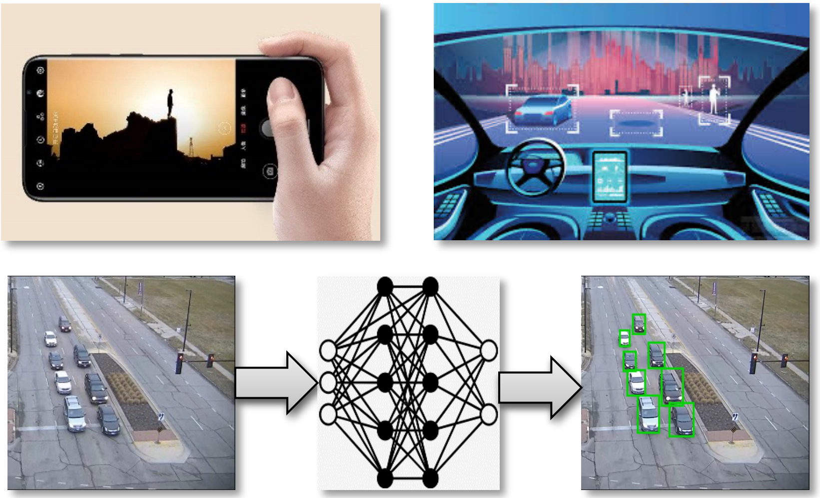
Crowdsourcing

- Crowdsourcing: Crowd + Outsourcing
  - Turning to a Crowd of People to Obtain the Needed Data or Data Analysis Services
    - ✓ E.g., Survey, Idea Competition, Wikipedia
  - Basic Components: Task Requestor, Platform, Worker



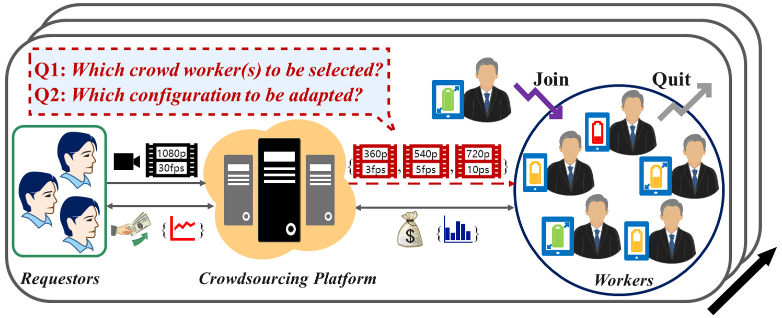
Video Analytics

- Workers Equipped with Mobile Devices for Video Analytics
  - Mobile Devices: Mobile Phone, Tablets, Intelligent Vehicle
  - Video Analytics: Computer Vision Methods (e.g., Object Detection, Identification and Tracking) based on DNN Models (e.g., YOLO)
  - Typical Applications: Image Labelling, Mobile Sensing and Traffic Prediction

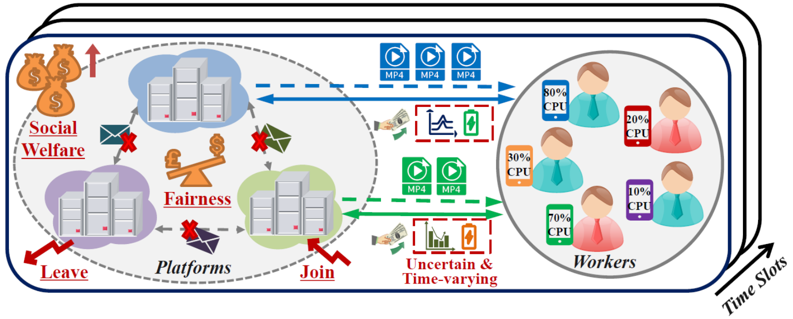


Crowdsourcing for Video Analytics

- Crowdsourcing for Video Analytics
  - Platforms hire proper workers, send video data to them, and select the configurations (frame rates, resolutions and models) to maximize their profits
- Existing Related Works:
  - Type 1: Address Conflicts among Workers
    - ✓ E.g., LOL [Infocom'22], LOL-C [TMC'24]
  - Type 2: Address Conflicts among Platforms
    - ✓ E.g., Crowd2 [Infocom'23]
- **Research Gap:**
  - Conflicts between platforms and workers can arise



Conflicts among workers where some workers may not be selected by platform



Conflicts among platforms where multiple platforms may select the same workers

Conflicts between Platforms and Workers

- Different Optimization Goals when Determining Video Analytics Configurations
  - Platforms recruit workers and strategically select the configurations to maximize their accuracy-based profits
  - Workers can flexibly accept the task or not, and tailor the configurations for their energy consumption-related individual gains

Conflicts between Platforms and Workers

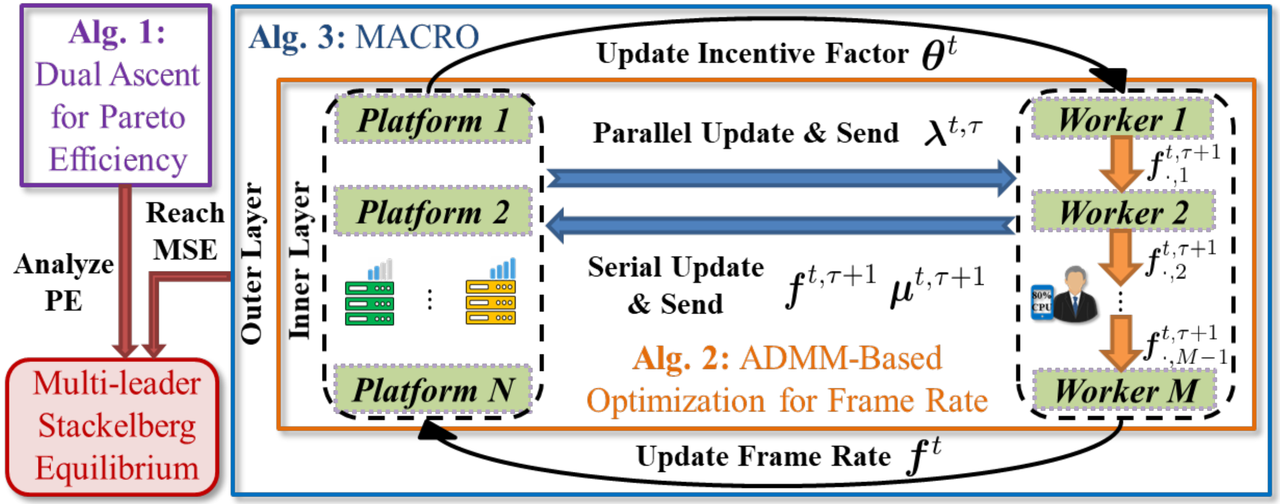
- **Problem Formulation:**
  - Determine the video analytics configuration: frame rate $0 \le f_{n,m} \le F_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}$
  - For each platform $n \in \mathcal{N}$, the optimization problem is formulated as
    - ✓ $\mathbb{P}_{1,n}^{\mathrm{p}}$: $\boxed{\max_{\boldsymbol{f}_{n,\cdot}} U_n^{\mathrm{p}}(\boldsymbol{f}_{n,\cdot}) = \sum_{m=1}^{M} u_{n,m}^{\mathrm{p}}(f_{n,m}) = \sum_{m=1}^{M} G_n(a_{n,m})}$ Accuracy-Based Profits
    - ✓ s.t. $\boxed{\sum_{m=1}^{M} \frac{f_{n,m}}{F_n} R_n b_{n,m} \le B_n}$ Limited Bandwidth Budgets for Video Data Transmission
  - Meanwhile, the optimization problem for each worker $m \in \mathcal{M}$ is formulated as
    - ✓ $\mathbb{P}_{1,m}^{\mathrm{w}}$: $\boxed{\max_{\boldsymbol{f}_{\cdot,m}} U_m^{\mathrm{w}}(\boldsymbol{f}_{\cdot,m}) = \sum_{n=1}^{N} u_{n,m}^{\mathrm{w}}(f_{n,m}) = \omega_m(e_m^{\mathrm{d}} + e_m^{\mathrm{c}})}$ Gains Related to Energy Consumption of Downloads and Computations
    - ✓ s.t. $\boxed{\sum_{n=1}^{N} f_{n,m} c_{n,m} \le C_m}$ Constrained Computing Resource for Video Analytics

30%
CPU

- **Major Challenge:**
  - It's hard for platforms to optimally determine workers' video analytics configurations for maximum accuracy-based profits while considering workers' energy-related gains

Overview of Our Work: MACRO

- Multi-Platform Game for Pareto Efficiency (PE)
  - [Alg. 1] For multi-platform game, we achieve the Pareto efficiency for platforms via a dual ascent-based method to determine proper video analytics configurations
- Incentivized Multi-Leader Game for Multi-Leader Stackelberg Equilibrium (MSE)
  - [Alg. 2, Alg. 3] For multi-leader game, we design the incentive function and its incentive factor updating strategy, and present an incentive maximization method, reaching MSE



Multi-Platform Game for Pareto Efficiency

- Before additionally considering workers' individual gains, we first maximize platforms' accuracy-based profits via a dual ascent-based approach (Alg. 1)
  - **Main Idea:** Maximize the Social Welfare of All Platforms, $\sum_{n=1}^{N} U_n^{\mathrm{P}}(\boldsymbol{f}_{n,\cdot})$
  - **Theoretical Analysis:** Pareto Efficiency can be achieved by Alg. 1, where no platform can change its strategy to increase its payoff without decreasing others' in multi-platform game

Algorithm 1: Dual Ascent for PE in Multi-platform Game

Input: $R_n, b_{n,m}, F_n, B_n, c_{n,m}, C_m, \forall n \in \boldsymbol{\mathcal{N}}, m \in \boldsymbol{\mathcal{M}}$

$t \leftarrow 0$, and Randomly Initialize $\boldsymbol{f}^0$, $\boldsymbol{\lambda}^0$ and $\boldsymbol{\mu}^0$;

while $t < T_{max}$ **do**

  $\boldsymbol{f}^{t+1} \leftarrow \arg\min_{\boldsymbol{f}} \mathcal{L}(\boldsymbol{f}, \boldsymbol{\lambda}^t, \boldsymbol{\mu}^t)$;

  $\lambda_n^{t+1} \leftarrow \lambda_n^t - \eta(\sum_{m=1}^{M} \frac{R_n b_{n,m}}{F_n} f_{n,m}^{t+1} - B_n), \forall n \in \boldsymbol{\mathcal{N}}$;

  $\mu_m^{t+1} \leftarrow \mu_m^t - \eta(\sum_{n=1}^{N} c_{n,m} f_{n,m}^{t+1} - C_m), \forall m \in \boldsymbol{\mathcal{M}}$;

  $t \leftarrow t + 1$;

Output: $\boldsymbol{f}^{T_{max}}$.

Optimize the Social Welfare by Dual Ascent-Based Update

Incentivized Multi-Leader Game for MSE

- Considering workers' gains inconsistent with platforms', workers are encouraged to contribute to platforms' Pareto efficiency via an incentive-based method
  - Two Layer Iteration (**Inner Layer for Workers** + Outer Layer for Platforms):
    - ✓ Inner Layer (Alg. 2): Workers' Updating their Frame Rates $\boldsymbol{f}$
      - ➢ Design **Incentive Function** for Worker $m \in \mathcal{M}$: Covering Worker's Utility, Platform's Utility and Incentive Value
        - » $I_m(\boldsymbol{\theta}_{\cdot,m}, \boldsymbol{f}_{\cdot,m}) = \sum_{n=1}^{N}(u^{\mathrm{p}}_{n,m}(f_{n,m}) + u^{\mathrm{w}}_{n,m}(f_{n,m}) + (\hat{I} - \theta_{n,m} f_{n,m}))$
      - ➢ **Main Idea:** Maximize the Sum of All Workers' Incentive Functions, $\sum_{m=1}^{M} I_m(\boldsymbol{\theta}_{\cdot,m}, \boldsymbol{f}_{\cdot,m})$

Algorithm 2: ADMM-based Optimization for Frame Rate

Input: $t, \boldsymbol{\theta}^t, \boldsymbol{f}^{t-1}, \boldsymbol{\lambda}^{t-1}, \boldsymbol{\mu}^{t-1}$

$\tau \leftarrow 0, (\boldsymbol{f}^{t,0}, \boldsymbol{\lambda}^{t,0}, \boldsymbol{\mu}^{t,0}) \leftarrow (\boldsymbol{f}^{t-1}, \boldsymbol{\lambda}^{t-1}, \boldsymbol{\mu}^{t-1})$;

while $\tau < \tau_{max}$ **do**

  `// Serial Update at Workers:`

  for *worker* $m = 1, 2, ..., M$ **do**

    Update $\boldsymbol{f}^{t,\tau+1}_{\cdot,m}$ and $\mu^{t,\tau+1}_{m}$ upon Eqs. (19), (20);

  `// Parallel Update at Platforms:`

  for *platform* $n = 1, 2, ..., N$ **do**

    Update $\lambda^{t,\tau+1}_{n}$ following Eq. (21);

  $\tau \leftarrow \tau + 1$;

Output: $\boldsymbol{f}^{t,\tau_{max}}, \boldsymbol{\lambda}^{t,\tau_{max}}, \boldsymbol{\mu}^{t,\tau_{max}}$.

Optimize the Sum of All Workers' Incentive Functions

Incentivized Multi-Leader Game for MSE

- Considering workers' gains inconsistent with platforms', workers are encouraged to contribute to platforms' Pareto efficiency via an incentive-based method
  - Two Layer Iteration (Inner Layer for Workers + **Outer Layer for Platforms**):
    - ✓ Outer Layer (Alg. 3): Platforms' Updating their Incentive Factors $\boldsymbol{\theta}$
      - ➢ **Design Goal:** How to motivate workers to contribute to platforms' PE when maximizing their incentives?
      - ➢ **Recall:** Workers' Incentive Functions

        How to offset each other?

        » $I_m(\boldsymbol{\theta}_{\cdot,m}, \boldsymbol{f}_{\cdot,m}) = \sum_{n=1}^{N}(u^{\mathrm{p}}_{n,m}(f_{n,m}) + u^{\mathrm{w}}_{n,m}(f_{n,m}) + (\hat{I} - \theta_{n,m} f_{n,m}))$
      - ➢ **Main Idea:** Leverage the **Marginal Utility** of Workers to Update the Incentive Factors $\theta^{t+1}_{n,m} = \frac{\mathrm{d}u^{\mathrm{w}}_{n,m}(f^{t}_{n,m})}{\mathrm{d}f_{n,m}}$

Algorithm 3: Incentive Mechanism MACRO for MSE

Input: $R_n, b_{n,m}, F_n, B_n, c_{n,m}, C_m, \forall n \in \boldsymbol{\mathcal{N}}, m \in \boldsymbol{\mathcal{M}}$

$t \leftarrow 0$, and Randomly Initialize $\boldsymbol{f}^0$, $\boldsymbol{\lambda}^0$ and $\boldsymbol{\mu}^0$;

while *Inequation (23) upon* $\boldsymbol{f}^t$ *is Not Satisfied* **do**

    // Update Incentive Factors:

    for *platform* $n = 1, 2, ..., N$ **do**

        Update $\theta^{t+1}_{n,m}, \forall m \in \boldsymbol{\mathcal{M}}$ following Eq. (22);

    // Update Frame Rate Decisions:

    $t \leftarrow t + 1$;

    Invoke **Alg. 2** with Input $(t, \boldsymbol{\theta}^t, \boldsymbol{f}^{t-1}, \boldsymbol{\lambda}^{t-1}, \boldsymbol{\mu}^{t-1})$, and Output $(\boldsymbol{f}^{t,\tau_{max}}, \boldsymbol{\lambda}^{t,\tau_{max}}, \boldsymbol{\mu}^{t,\tau_{max}})$;

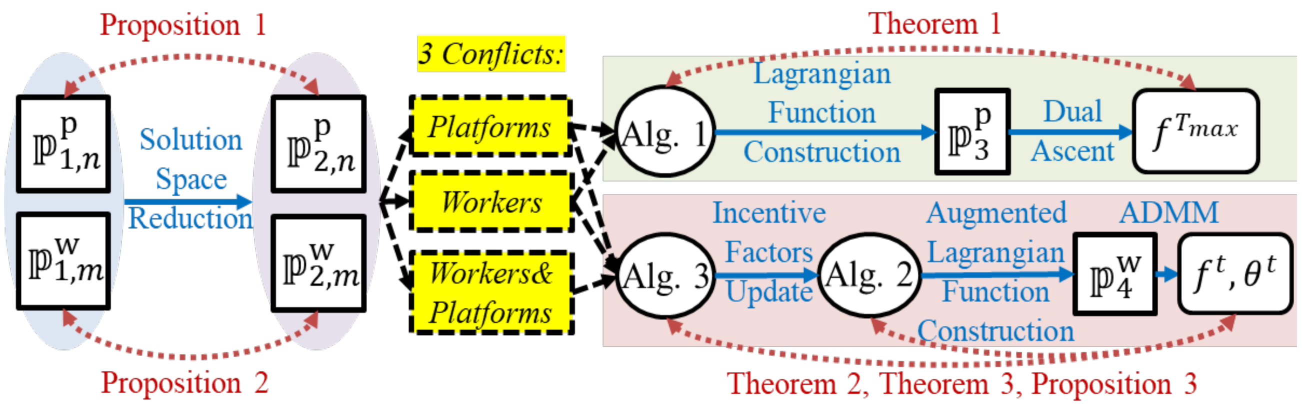
    $(\boldsymbol{f}^t, \boldsymbol{\lambda}^t, \boldsymbol{\mu}^t) \leftarrow (\boldsymbol{f}^{t,\tau_{max}}, \boldsymbol{\lambda}^{t,\tau_{max}}, \boldsymbol{\mu}^{t,\tau_{max}})$;

Output: $\boldsymbol{f}^t, \boldsymbol{\theta}^t$.

Optimize the Incentive Factors

Incentivized Multi-Leader Game for MSE

- Considering workers' gains inconsistent with platforms', workers are encouraged to contribute to platforms' Pareto efficiency via an incentive-based method
  - Two Layer Iteration (**Inner Layer for Workers + Outer Layer for Platforms**)
  - **Theoretical Analysis:**
    - ✓ **Multi-leader Stackelberg equilibrium** can be achieved
    - ✓ Specifically, platforms' Pareto efficiency is guaranteed, and none of the platforms and workers have incentives to alter their strategies for higher payoff when others' keep unchanged



Evaluation

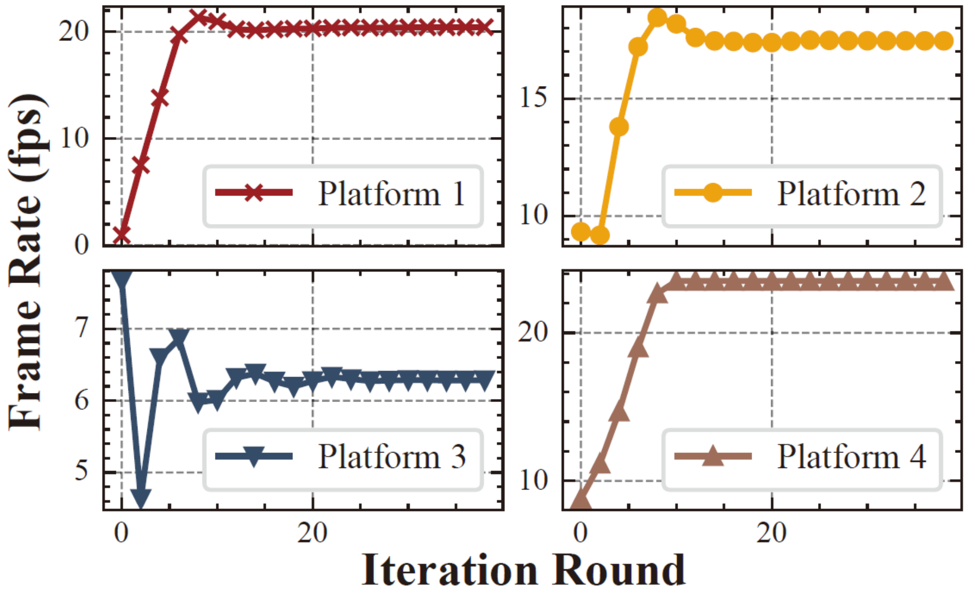
- Trace-Driven Experiments
  - Video Dataset AICity and PANDA, yolov7 models, F1-Score based Accuracy
  - Transmission Energy $\sim N(5,0.5)\times 10^{-6}$ J, Computation Energy $\sim N(5,0.5)$ J per Frame
  - Revenues G_n and ω_m Generated from Sales Product Dataset
  - Bandwidth Budget B_n in $[10, 25]$, Computation Capacity C_m in $[3, 21]$

- Evaluated:
  - How does Alg. 1 converge for Pareto efficiency?
  - How do Alg. 2 and Alg. 3 converge for multi-leader Stackelberg equilibrium?
  - How is the scalability of MACRO?

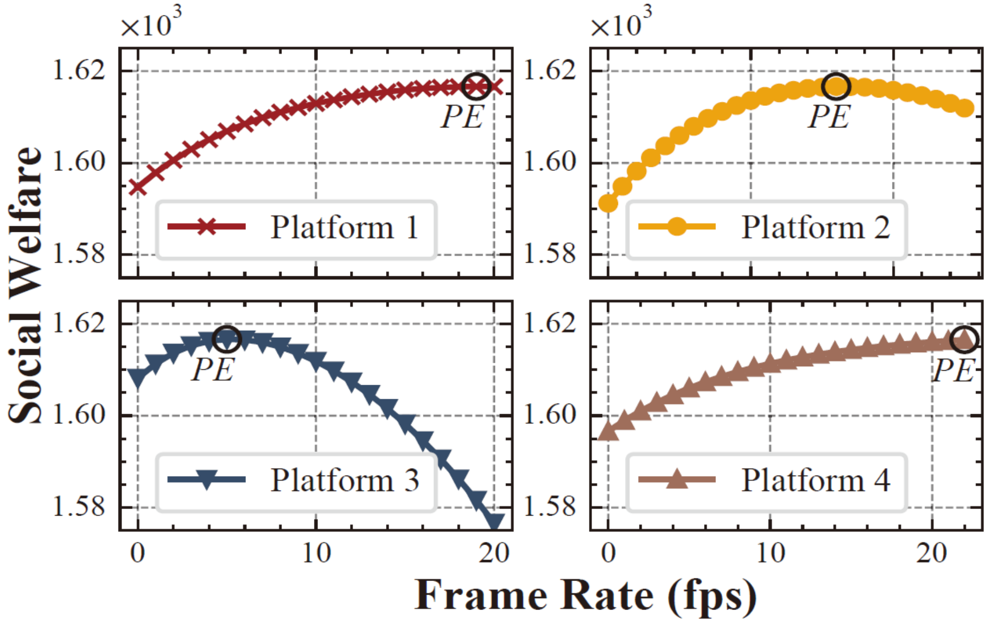
Converge for Pareto efficiency

- How does Alg. 1 converge for Pareto efficiency?

Platform cannot changes its frame rate to improve the social welfare



Convergence of Frame Rate

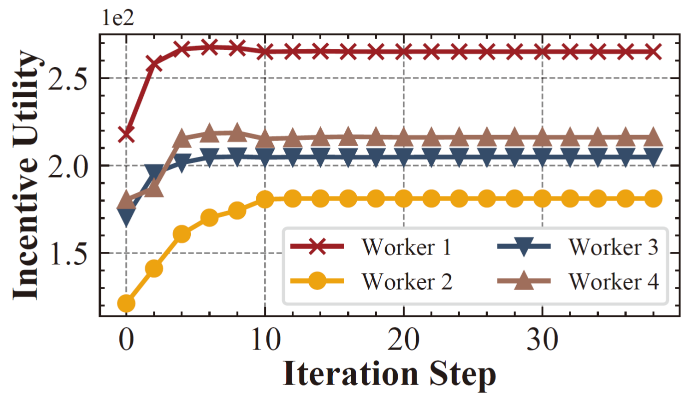


Pareto Efficiency

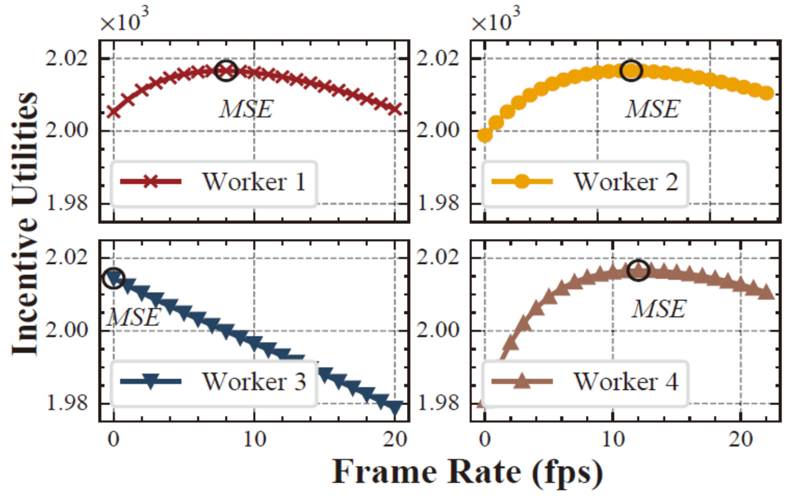
Converge for MSE

- How do Alg. 2 and Alg. 3 converge for multi-leader Stackelberg equilibrium?

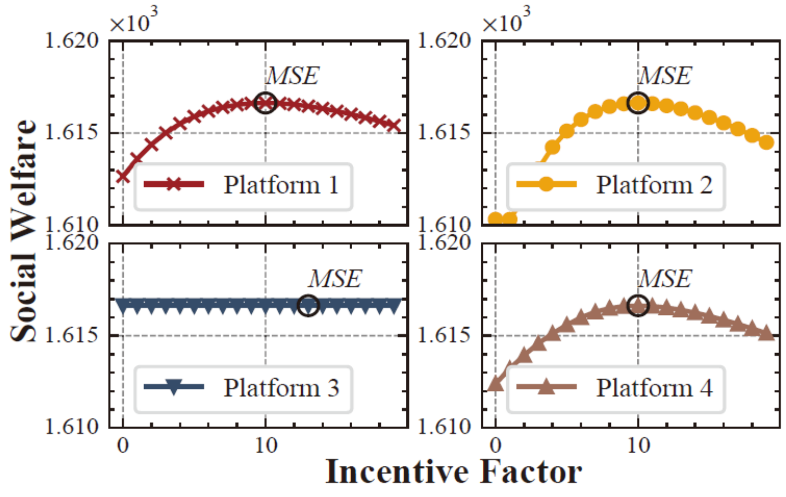
Worker and platform cannot change their strategies to raise their utility



Convergence of Incentive Utility



MSE for Workers

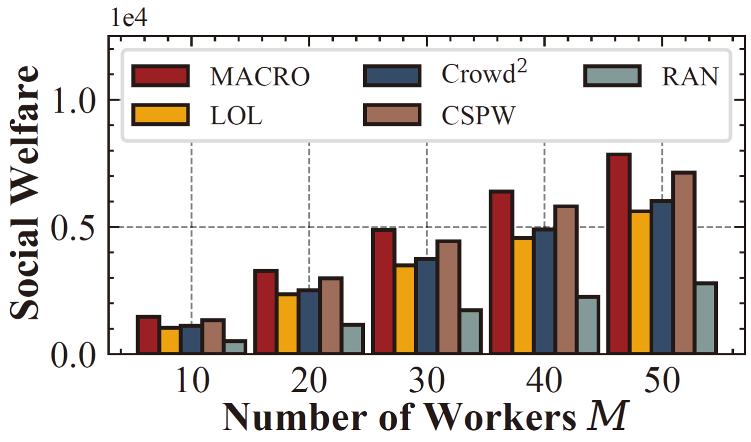


MSE for Platforms

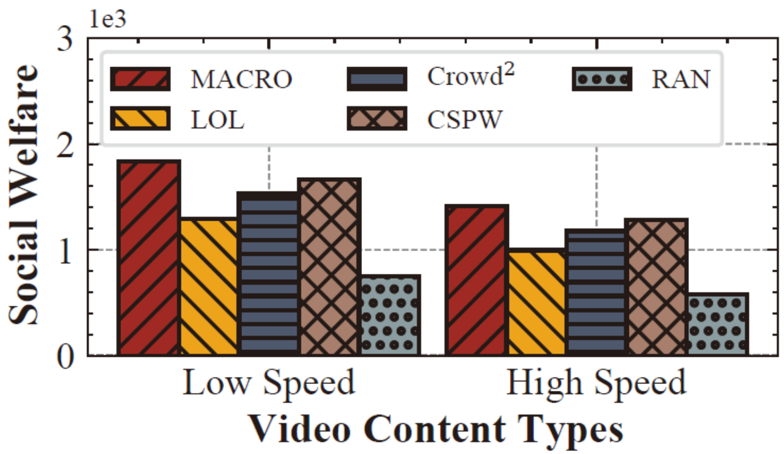
Scalability of MACRO

- How is the scalability of MACRO?

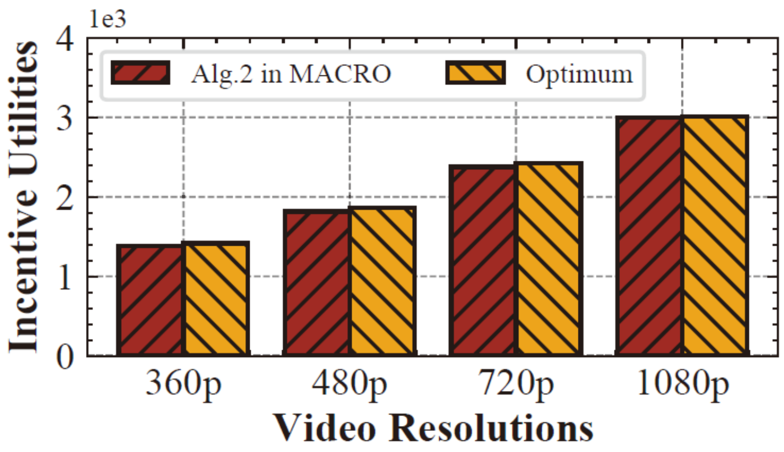
MACRO improves the social welfare by 26% on average



Varying Number of Workers



Various Video Content Types



Various Video Resolution

Conclusion

- MACRO: firstly considering the platform-worker conflicts for video analytics tasks upon crowdsourcing
  - **For multi-platform game**, we achieve the **Pareto efficiency** for platforms via a dual ascent-based method to determine proper video analytics configurations
  - **For multi-leader game**, we design the incentive function and its incentive factor updating strategy, and present an incentive maximization method, reaching the **multi-leader Stackelberg equilibrium**