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
  – Basic Components: Task Requestor, Platform, Worker

Get Results from Mechanical Turk Workers
- Ask workers to complete HITs – Human Intelligence Tasks – and get results using Mechanical Turk. Get started.

As a Mechanical Turk Requester you:
- Have access to a global, on-demand, 24×7 workforce
- Get thousands of HITs completed in minutes
- Pay only when you’re satisfied with the results

Make Money by working on HITs
- HITs – Human Intelligence Tasks – are individual tasks that you work on. Find HITs now.

As a Mechanical Turk Worker you:
- Can work from home
- Choose your own work hours
- Get paid for doing good work

Get your account, Load your tasks, Get results

Requestors Platforms Worker Pool

2024/6/12
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 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 $0 \leq f_{n,m} \leq F_n, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}$
  
  - For each platform $n \in \mathcal{N}$, the optimization problem is formulated as
    
    \[
    \mathcal{P}^P_{1,n} : \max_{f_{n}} U^P_n(f_{n}) = \sum_{m=1}^{M} u^P_{n,m}(f_{n,m}) = \sum_{m=1}^{M} G_n(a_{n,m})
    \]
    
    \[
    \text{s.t.} \sum_{m=1}^{M} \frac{f_{n,m}}{F_n} R_n b_{n,m} \leq B_n
    \]
    
    - Meanwhile, the optimization problem for each worker $m \in \mathcal{M}$ is formulated as
      
      \[
      \mathcal{P}^W_{1,m} : \max_{f_{m}} U^W_m(f_{m}) = \sum_{n=1}^{N} u^W_{n,m}(f_{n,m}) = \omega_m(e^d_m + e^c_m)
      \]
      
      \[
      \text{s.t.} \sum_{n=1}^{N} f_{n,m} c_{n,m} \leq C_m
      \]

• **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

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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, $\sum_{n=1}^{N} U_n^P (f_n,.)$

  – **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

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**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 \mathcal{N}, m \in \mathcal{M}
1 t \leftarrow 0, and Randomly Initialize f^0, \lambda^0 and \mu^0;
2 while t < T_{max} do
3 \quad f^{t+1} \leftarrow \arg \min_{f} \mathcal{L}(f, \lambda^{t}, \mu^{t});
4 \quad \lambda_{n}^{t+1} \leftarrow \lambda_{n}^{t} - \eta(\sum_{m=1}^{M} \frac{B_{n,m} - f_{n,m}^{t+1} - B_{n}}{F_{n,m}}), \forall n \in \mathcal{N};
5 \quad \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 \mathcal{M};
6 \quad t \leftarrow t + 1;
```

Output: $f_{T_{max}}$.
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 $f$
      
      **Design Incentive Function** for Worker $m \in \mathcal{M}$: Covering Worker’s Utility, Platform’s Utility and Incentive Value
      
      $$l_m(\theta, m, f, m) = \sum_{n=1}^{N} u_{n,m}^P(f_{n,m}) + u_{n,m}^W(f_{n,m}) + (i - \theta_{n,m}f_{n,m})$$
      
      **Main Idea**: Maximize the Sum of All Workers’ Incentive Functions, $\sum_{m=1}^{M} l_m(\theta, m, f, m)$

      **Algorithm 2**: ADMM-based Optimization for Frame Rate
      
      ![Algorithm 2](image)

      **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 $\theta$
      - **Design Goal:** How to motivate workers to contribute to platforms’ PE when maximizing their incentives?
      - **Recall:** Workers’ Incentive Functions
        - $I_m(\theta, m, f, m) = \sum_{n=1}^{N} u_{n,m}^P(f_{n,m}) + u_{n,m}^W(f_{n,m}) + (\hat{l} - \theta_{n,m}f_{n,m})$
      - **Main Idea:** Leverage the Marginal Utility of Workers to Update the Incentive Factors $\frac{\partial u_{n,m}^W(f_{n,m})}{\partial f_{n,m}}$

**Algorithm 3:** Incentive Mechanism MACRO for MSE

- **Input:** $R_n, b_{n,m}, F_n, B_n, c_{n,m}, C_n, \forall n \in N, m \in M$
- $t \leftarrow 0$, and Randomly Initialize $f^0$, $\lambda^0$ and $\mu^0$;
- **while Inequation (23) upon $f^t$ is Not Satisfied do**
  - **Update Incentive Factors:**
  - $t \leftarrow t + 1$;
  - Invoke Alg. 2 with Input $(t, \theta^t, f^{t-1}, \lambda^{t-1}, \mu^{t-1})$, and Output $(f^{t, \tau_{max}}, \lambda^{t, \tau_{max}}, \mu^{t, \tau_{max}})$;
  - $(f^t, \lambda^t, \mu^t) \leftarrow (f^{t, \tau_{max}}, \lambda^{t, \tau_{max}}, \mu^{t, \tau_{max}})$;
- **Output:** $f^t, \theta^t$. 

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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 $\sim N(5,0.5) \times 10^{-6} \text{ J}$, Computation Energy $\sim N(5,0.5) \text{ J per Frame}
  – Revenues $G_n$ and $\omega_m$ 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 change its frame rate to improve the social welfare.
Converge for MSE

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

Convergence of Incentive Utility

MSE for Workers

MSE for Platforms

Worker and platform cannot change their strategies to raise their utility
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