Overview: Reinforcement Learning in Crowdsourcing and Crowdsensing

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Problem Introduction

- Motivation:
  - Proposal of novel reinforcement learning (RL) methods
  - Effective and efficient approximations are hard to design
  - Task assignment and worker arrangement can be modeled as MDP
- Difficulties:
  - Deep learning, especially Deep RL, has much higher computation costs than simple heuristic algorithms
  - It's hard to achieve significant improvements on the state-of-the-art models using approximation algorithms
  - The design and training of networks can be really tricky

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Recent Work

- 2020 ICDE:
  - Curiosity-Driven Energy-Efficient Worker Scheduling in Vehicular Crowdsourcing: A Deep Reinforcement Learning Approach
  - An End-to-End Deep RL Framework for Task Arrangement in Crowdsourcing Platforms
- 2020 CIKM:
  - Auxiliary-task Based Deep Reinforcement Learning for Participant Selection Problem in Mobile Crowdsensing
- 2020 PerCom:
  - Participants Selection for From-Scratch Mobile Crowdsensing via Reinforcement Learning

Recent Work

- 2020 IEEE Internet Things of Journal:
  - Energy-Efficient Mobile Crowdsensing by Unmanned Vehicles: A Sequential Deep Reinforcement Learning Approach
- 2019 DASFAA:
  - Reinforced Reliable Worker Selection for Spatial Crowdsensing Network
- 2019 Computer Networks:
  - Reinforcement Learning-Based Cell Selection in Sparse Mobile Crowdsensing (From ICDCS 2018)

Recent Work

- Common RL methods:
  - Multi-Arm Bandit (MAB)
  - Deep Q Network (DQN)
  - Proximal Policy Optimization (PPO)

- Deep RL is utilized in almost every work

- Most works use RNN and attention transformer

- Sometimes the real world is formulated as rectangular grids and CNN is used to extract spatial patterns

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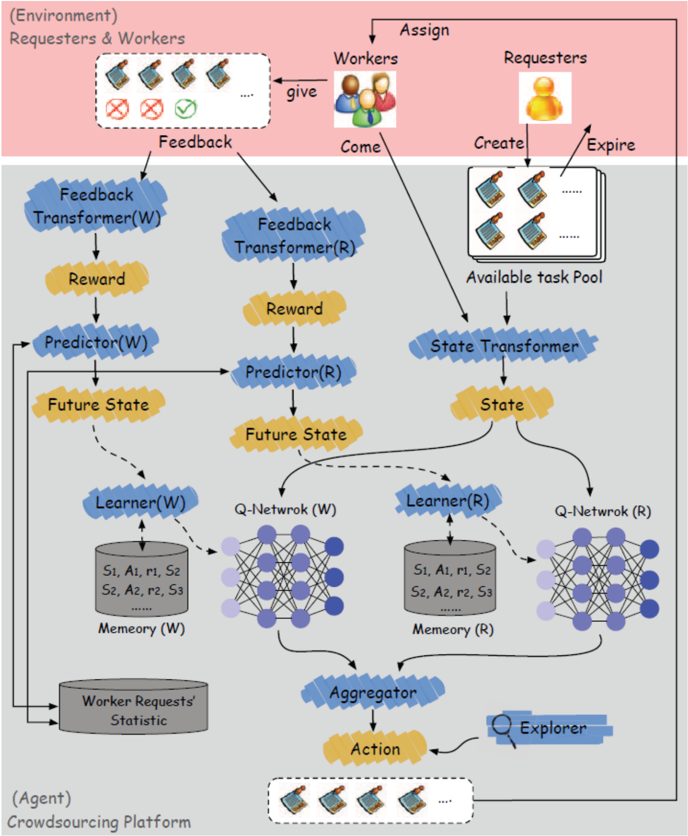
Typical Model I

- Title: An End-to-End Deep RL Framework for Task Arrangement in Crowdsourcing Platforms
- Conference: ICDE, 2020
- RL Algorithm: Double Deep Q Network (Double DQN)
- Network Kernel: Attention transformer

Model Overview

- At timestamp i, a worker w_i comes and there is an available task set $\{T_i\}$. (So a timestamp is triggered by a coming worker)
- w_i has a feature f_{w_i} (completion history) and a quality q_{w_i}
- The model contains two different Q networks to optimize MDP (w) and MDP (r)



Flow Chart of Model

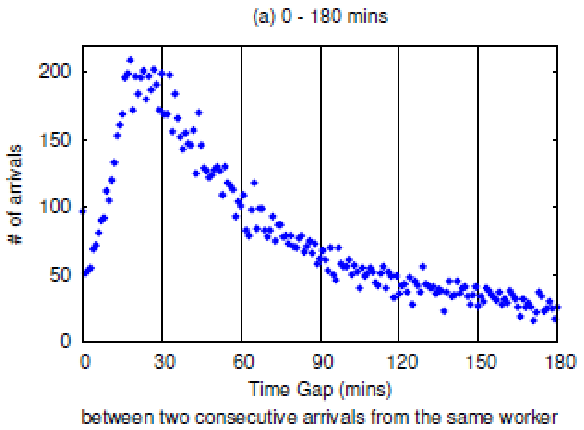
MDP for Workers

- MDP (w):
  - State $s_i = f_{w_i}$
  - Action $a_i = t_{ij}$ or $a_i = \sigma(T_i) = \{t_{i1}, t_{i2}, \cdots\}$
  - Reward $r_i = \begin{cases} 1, & if\ w_i\ completes\ t_{ij} \\ 0, & otherwise \end{cases}$
  - Future state s_{i+1} happens when w_i comes again
- From the definition of MDP (w), the objective is to optimize the cumulative completion rate of workers in the long run.

Problem in MDP (w)

- Parameters in Q-network(w) are shared by all workers
- We need to predict s_{i+1} so that we can update immediately

- Learn the distribution $\phi(g)$ for Time_{i+1}
- Check for expired tasks and compute r_{i+1}
- Use expectation to update the parameters



Distribution $\phi(g)$ in History

MDP for Requesters

- MDP (r):
  - State $s_i = [f_{w_i}, f_{T_i}, q_{w_i}, q_{T_i}]$
  - Action $a_i = t_{ij}$ or $a_i = \sigma(T_i) = \{t_{i1}, t_{i2}, \cdots\}$
  - Reward $r_i = \Delta q_i$ (quality gain)
  - Future state s_{i+1} happens when the next worker w_{i+1} comes
- From the definition of MDP (r), the objective is to optimize the cumulative quality gain of tasks in the long run.

Problem in MDP (r)

- There are too many possibilities for $(w_i, s_i, w_{i+1}, s_{i+1})$

- Similar to MDP (w), learn $\varphi(g)$ from history
- Learn the rate of new workers p_{new}
- Obtain the probability for a coming worker w:

$$\Pr(w_{i+1} = w) = \begin{cases} (1 - p_{new}) \dfrac{\phi(g_w)}{\sum_{w' \in W_{old}} \phi(g_{w'})}, & w \in W_{old} \\ p_{new}, & w \text{ is new} \end{cases}$$

- Use summation over g and w to update the parameters

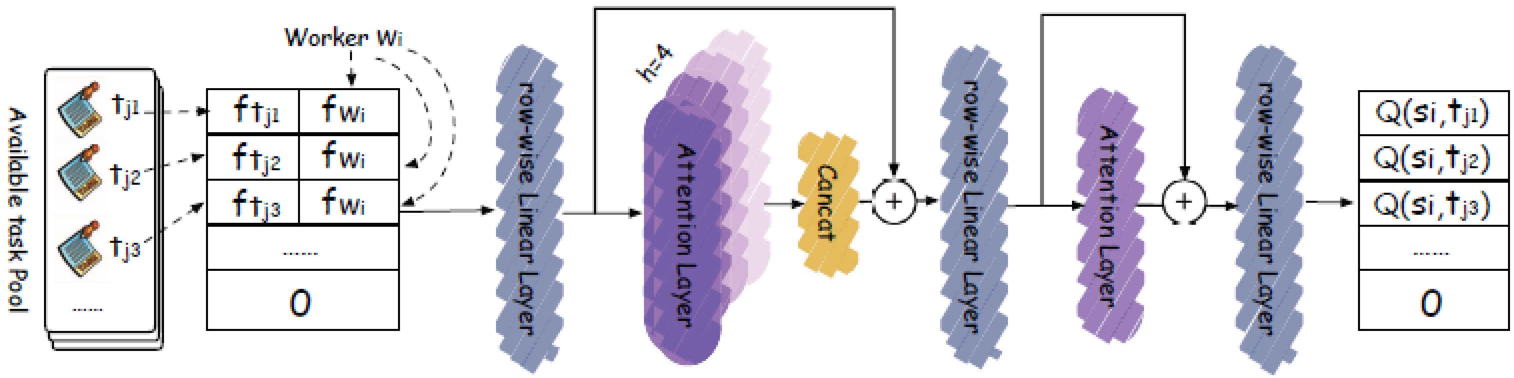
Q Networks

- Network structure:

- Challenges:
  - The number of tasks (input size) are not fixed
  - The order of tasks should not affect the output
  - The value of a task is influenced by others

Q Networks

- Network structure:



- Solutions:
  - Set maximum number of available tasks & Use zero padding
  - Use multi-head self-attention layer
  - Structures to enhance the stability and learning ability

Typical Models II

- Title: Energy-Efficient Mobile Crowdsensing by Unmanned Vehicles: A Sequential Deep Reinforcement Learning Approach
- Journal: IEEE Int. Things of Journal, 2020
- RL Algorithm: PPO + Actor-Critic
- Network Kernel: CNN + LSTM

Optimization Object

- Energy efficiency of the entire system at timestamp t as

$$\alpha_t = \frac{\beta_t f_t}{e_t}$$

- β_t: Data collection ratio
- f_t: Jane's fairness index
- e_t: Energy consumption ratio

POMDP Formulation

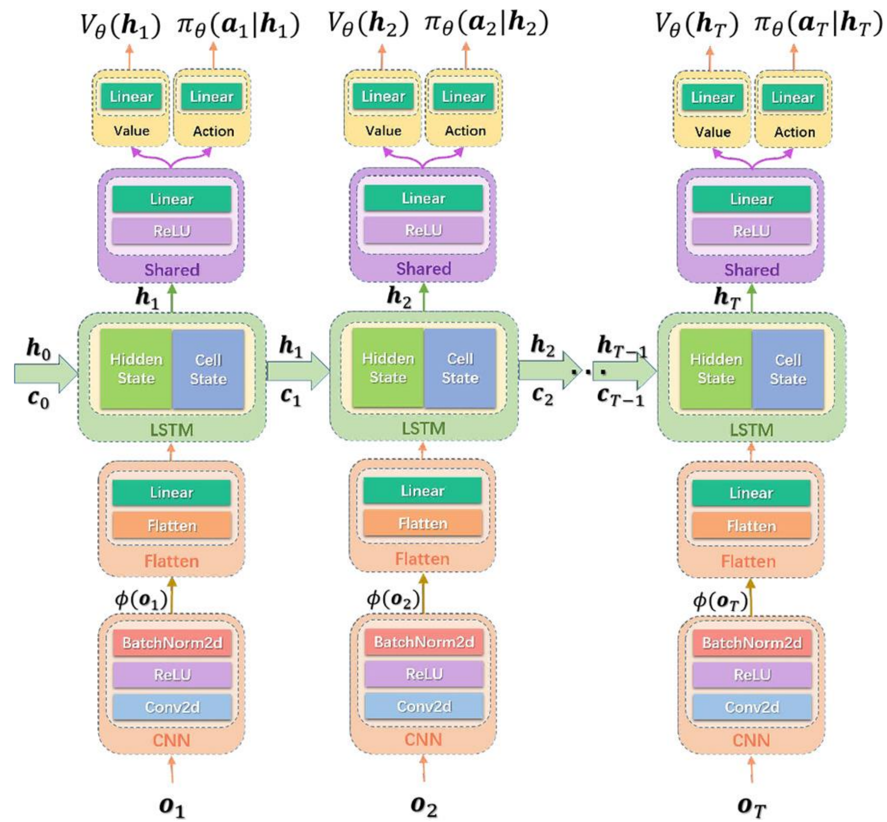
- Observation: o_t is a 3-D vector in size $m \times n \times 3$
  - The real-world 2-D positions are mapped to $m \times n$ grids
  - Channel 1 contains obstacles (-1) and sensor nodes (data)
  - Channel 2 contains UVs (energy) and charging stations (-1)
  - Channel 3 contains sensor nodes (visit times till timeslot t)
  - Other positions are filled with 0

POMDP Formulation

- Action: $a_t = [a_t^1, a_t^2, \cdots, a_t^V]$, where $a_t^v \in \mathbf{R}^3$
  - $a_t^v(0)$ and $a_t^v(1)$ denotes moving distance and direction of v
  - $a_t^v(2)$ denotes charging (> 0) or collecting data (< 0)
- Reward: $r_t = \frac{1}{V}\sum_v (r_t^v + p_t^v)$
  - v gets reward $r_t^v = f_t \frac{\Delta d_t^v}{\eta_l \Delta d_t^v + \eta_d \Delta l_t^v}$
  - v gets penalty p_t^v when it hits obstacles or runs out of energy

Policy Network

- Use CNN structure to extract spatial patterns
- Flatten and linearly map 3-D features to 1-D features
- LSTM generates h_t and c_t with historical h_{t-1} and c_{t-1}
- Obtain $\pi_\theta(a_t|h_t)$ and $V_\theta(h_t)$



Loss function: $L_t(\theta) = E_t[L_t^{CLIP}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](h_t)]$

Training Process

- In each iteration (episode), we collect N pieces of transition which have a length T and split them into pieces of length k.
- With smaller pieces, we optimize the loss function in minibatch manners and update parameters of the network.

Algorithm 1: Proposed Algorithm: PPO+LSTM

for *iteration=1,2,...* **do**
  for i=1,2,...,N **do**
    for t=1,2,...,T **do**
      Get an observation $\boldsymbol{o}_{t,i}$ from environment i;
      Use Eqns. (12a, 12b, 12c) to acquire the action distribution $\pi_{\theta_{old}}(\boldsymbol{a}_{t,i}|\boldsymbol{h}_{t,i})$;
      Sample an action $\boldsymbol{a}_{t,i}$ using above distributions;
      Take action $\boldsymbol{a}_{t,i}$ in environment i and get reward $r_{t,i}$;
    Use Eqns. (13d, 13e, 12d) to compute advantage estimates $A^h_{1:T,i}$;
    Collect trajectory $\tau_{1:T,i}$;
  Split trajectories $\tau_{1:T,1:N}$ as $\mathcal{T} = \{\tau_{1:k,1:N}, \tau_{2:(k+1),1:N}, \ldots, \tau_{(T-k):T,1:N}\}$;
  Optimize surrogate $J_t^{CLIP+VF+S}(\theta)$ in Eqn. (13) with respect to θ, with K epochs with random minibatch size $M \leq N(T-k)$;
  $\theta_{old} \leftarrow \theta$;

PPO Network Optimization

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Personal Research

- Some previous work have paid attention to the fairness of data collection at all PoIs in crowdsensing space.
- My recent focus is to build an RL framework, which can effectively optimize an objective in crowdsensing system while keeping the load of all sensing devices balanced.
- At present I am to formulate a valuable and available problem.
- Co-workers are very welcome !!!

Another Direction

- Up till now, little focus on Multi-Agent RL approaches
- On behalf of the platform, MARL looks suitable
- Local observation indicates better privacy protection?
- “Cooperation” between workers leads to better solution?
- I might look into this type of model in a short time.

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Summary

- The introduction of applying (Deep) RL in scheduling problem of crowdsourcing and crowdsensing
- Recent work and approaches on this topic
- Two representative models proposed this year
- Progress of my own research

Thanks！