Dynamic Incentive Mechanism Design for COVID-19 Social Distancing

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Abstract

As countries enter the endemic phase of COVID-19, people's risk of exposure to the virus is greater than ever. There is a need to make more informed decisions in our daily lives on avoiding crowded places. Crowd monitoring systems typically require costly infrastructure. We propose a crowd-sourced crowd monitoring platform which leverages user inputs to generate crowd counts and forecast location crowdedness. A key challenge for crowd-sourcing is a lack of incentive for users to contribute. We propose a Reinforcement Learning based dynamic incentive mechanism to optimally allocate rewards to encourage user participation.

Introduction

At present, countries with high vaccination rates like Singapore are starting to restart their socio-economic activities by moving towards the endemic stage of COVID-19. They still face the risk of increasing infection numbers amid the COVID-19 mutations. The key way to limit the spread is still social distancing. There is a need to make more informed decisions in our daily lives (e.g., visiting less crowded places).

Crowd monitoring systems typically require investment in infrastructure, e.g., closed-circuit television (CCTV). However, this is expensive and lacks the mobility to monitor diverse locations. Alternatively, individuals can carry along devices such as Radio-frequency Identification (RFID) tags or permit location sharing using mobile phones. This provides a gauge on how crowded a place is. However, this approach requires wide adoption of such devices.

Recently, (Jiang et al. 2021; Teng et al. 2021) proposed a crowdsourced image-based solution to obtain information of the crowd situation at different locations. When visiting different areas of interest, users use their mobile phones to capture an image of the crowd situation. The images are analyzed for crowdedness levels and shared on the platform for everyone. Over time, as more users contribute to the platform, it is able to capture daily and weekly crowd patterns and provide forecasts for future time points. It is able to provide data-driven answers to questions like what is the best day of the week to visit different campus eateries (Teng et al. 2021). However, the system is reliant on contributions from the public. A key challenge for crowd-sourcing is a lack of incentive for users to contribute. This paper[1] improves on (Jiang et al. 2021) by introducing a Reinforcement learning-based budget-aware dynamic incentive mechanism to allocate reward points to maximize user uploads optimally.

System Design

The main features of *crowded.sg* are as follows:

1. *Current crowd conditions*: Users are presented with a map showing key locations of interest that are color coded based on how crowded they are (Fig. 1(a)). Users can click on location markers to view the latest uploaded images (Fig. 1(b)), which have been algorithmically blurred for privacy protection (Fig. 1(c)). Users are able to curate images by upvoting or downvoting.
2. *Predicted crowd level based on historical data*: We provide an estimate of the current crowd level for every hour of the week, displayed in the form of a heat map for weekly trends or bar graph for hourly trends (Fig. 1(d)).
3. *Dynamic point reward system and leaderboard*: To incentivize users to upload more frequently, a point reward system and a monthly leaderboard are incorporated. The number of points rewarded for each location is displayed inside the location marker, and users can toggle to display (Fig. 1(e)). Registered users can earn points and compete with other users in the leaderboard (Fig. 1(f)).

AI Engine

The AI engine contains a visual analytics module for crowd counting and a prediction module for forecasting the number of visitors at various locations.

The Vision module takes a hybrid approach by combining Mask R-CNN (He et al. 2017), an object detection model, and CSRNet (Li, Zhang, and Chen 2018), a density estimation method into a single workflow to handle both sparse and dense crowds.

The Predictive module models crowd trends using regression models to better deal with the irregular time series caused by missing data or outliers. Implemented using Prophet (Taylor and Letham 2018), an open-source forecasting library designed by Facebook.

[1]Demo video: https://youtu.be/4ilOeACyUHs

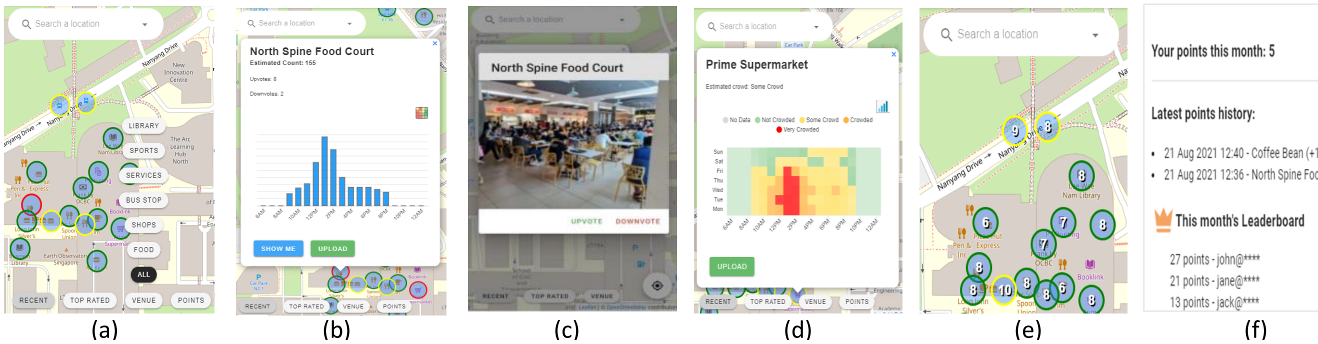

Figure 1: The *crowded.sg* user interaction design.

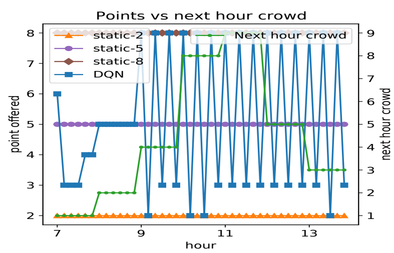

Figure 2: Schemes comparison.

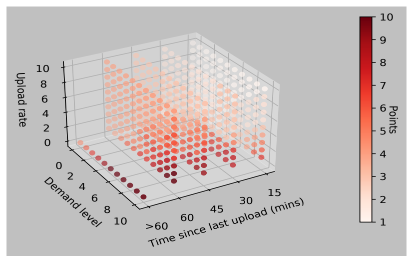

Figure 3: Points vs. States.

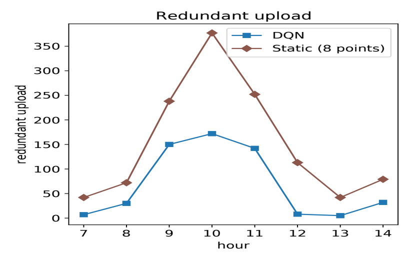

Figure 4: Redundant upload by hour.

The Incentive module chooses an appropriate amount of reward points to attract user uploads while minimizing incentive expense. The task can be considered as a sequential decision problem where the platform's demand for image sensing data and the supply of user uploads determine the points allocated for each location. The problem is formulated as a Markov Decision Process (MDP) (Bellman 1957). The state space is defined by the sensing demand (i.e., current crowd level, next hour crowd level, and click rate) and image upload supply (i.e., time since last upload and upload rate for the past hour). The agent (Yu, Shen, and Miao 2007) allocates points for each location and obtains greater rewards for increasing image uploads while keeping incentive expenses low. The MDP with unknown transition probability is solved using the Deep Q-Network (DQN) algorithm (Mnih et al. 2015), which uses the neural network to find the optimal policy by learning the state-action values.

Experimental Evaluation

The DQN is trained on platform usage data (collected using Google Analytics) and external data obtained from the Google Popular Times API We perform simulations based on a school canteen on a weekday from 00:00 AM to 23:59 PM. The crowd level can be observed in Fig. 2, with peak crowds observed during lunch hours. The number of participants using the platform are modelled to be a function of the crowd level. There are three tranches of participants, each with a willingness to upload only if the points awarded exceed their preference threshold. The preference threshold is arranged in an ascending order. At every 10 minutes interval, the agent will sense the environment and adjust the points offered.

The incentive scheme is observed to respond to the current system states. The points chosen by the agent can be visualised in Fig. 3. States with higher sensing demand and lower image upload supply are allocated higher points and vice versa. In contrast, static incentive schemes offered to users do not vary according to the current system states. Moreover, the dynamic incentive scheme also takes into account the *next hour* crowd level derived from historical data (Fig. 2). For example, the points awarded are adjusted upwards when the location is expected to become more crowded. This serves to encourage more uploads at the location so that users of the platform can make up-to-date informed decisions on whether to avoid the place.

The dynamic incentive scheme is also budget-aware. Less points are allocated for off-peak hours with less crowds. For places with up-to-date information, there will be fewer points offered for the next period to reduce the number of redundant uploads (Fig. 4).

Conclusions

We improve the crowd-sourced crowd monitoring platform by introducing a dynamic incentive mechanism to motivate user uploads. The increased contributions lead to more up-to-date information being shared on the platform and more data collected for training forecasting models. As a result, users can make more informed social distancing decisions.

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