GRAND-VISION: An Intelligent System for Optimized Deployment Scheduling of Law Enforcement Agents (System Demo)

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Abstract

Law enforcement agencies in dense urban environments, faced with a wide range of incidents and limited manpower, are turning to data-driven AI to inform their policing strategy. We present an intelligent patrol scheduling system called GRAND-VISION: Ground Response Allocation and Deployment - Visualization, Simulation, and Optimization. The system employs deep learning, trained on real historical incident data, to generate incident sets that are used to plan daily patrol schedules that can accommodate varying manpower, break times, manual pre-allocations, and a variety of spatio-temporal demand features. The complexity of the scenario results in a system with real world applicability, which we have developed in partnership with a large urban law enforcement agency. A video demo can be found at: https://youtu.be/jsxGKxXSeNs

System Overview

Public security organizations around the world are focusing on law enforcement based on the concept of ”Reactive to Proactive”. Some measurement concepts, such as “Visible Security”, which focuses on prediction (i.e. shortening arrival time to crime scene) and prevention (i.e. smart patrol) have been explored and conceptualized. With the aging of society and increasingly limited human resources, the solution to this challenge revolves around the use of technology to establish an efficient crime prediction, prevention, and response schedule. In this demonstration, we present a data-driven AI planning system, currently on trial with a local law enforcement agency (LEA) called GRAND-VISION (GV) that performs daily deployment scheduling of law enforcement agents. GRAND-VISION is an abbreviated name for Ground Response Allocation and Deployment - Visualization, Simulation, and Optimization. Details of the system can be found in (Chase et al. 2021) and a demo of the system is available at (Chase 2021). In essence the system harnesses historical incident data and other factors such as demographics and public holidays to predict the occurrence of incidents over time and space with high accuracy on a daily basis. Based on such prediction, as well as the daily supply of agent resources and other inputs, the system generates hourly deployment schedules that provide the best response to incidents, taking breaks and other constraints into consideration. Executing a deployment schedule on a daily basis allows law enforcement to be tailored to the demand characteristics of a given day, and makes it harder for criminals to anticipate where law enforcement agents will be. When special events occur, a daily deployment can accommodate manual pre-allocation of resources to areas determined by a commander, likewise, if break times need to be changed, or, manpower is short on a given day, it can be accommodated intelligently. This last point is particularly pertinent during the COVID-19 pandemic, when law enforcement manpower may be stretched thin due to the need to self-isolate after exposure, or to assist in contact tracing and enforcement of quarantine measures.

In the problem setting we consider, emergency incidents occur and are reported to a central dispatcher. The dispatcher assigns the nearest available agent to attend. Incidents may be classified as either urgent or non-urgent, with different response time targets associated with each. Some incidents require more than one agent to attend, and they must remain in attendance until the service time of the incident is complete, whereupon they return to the region they have been assigned to patrol. To ensure that as many incidents are attended within the target time as possible, we present a system that designs a deployment schedule that assigns agents to patrol locations throughout their shift. To create effective plans, the GV system executes a four step algorithm. First, the Incident Generator module produces sets of synthetic incidents, with each set corresponding to one scenario of the shift being planned for. Second, the Optimizer uses these incidents to identify the sectors that the available agents must be deployed to, with the output being the number of agents required in each sector on a 2-hourly basis. Third, the number of agents required in each sector is mapped to the set of actual agents by the Scheduler on an hourly basis, which aims to minimize the amount of movement agents are required to do while accounting for breaks. Finally a set of generated test incidents is used to evaluate the scheduled deployment using a dispatch Simulator.

Modules

The Incident Generator generates training data sets for the Optimizer. It uses a large set of incident data, provided by

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our partner LEA, containing details of incident timing, urgency, location (in lat-long coordinates), duration, and type, as well as the nature of the response, including the responding agents, and their response times. We combine this with other data such as demographics and land use features. A Ridge Regression model outputs the total daily incident count then, using a Generative Adversarial neural Network (GAN), we can output all other incident parameters.

The Optimizer performs an allocation of on-duty agents to locations to minimize the risk of failing an incident response, and we extract the number of agents required per location as input to the Scheduler. The response time minimization model is based on Sample Average Approximation (SAA), which produces a single solution that yields the best expected risk across all generated incident scenarios.

The Scheduler maps the Optimizer result to the list of agents on duty, taking into account their respective break times. The aim is to ensure that all required sectors have agent coverage so that the demand is met, employing an MIP to minimize the total travel time between sectors at the end of each time period. It assigns agents on a 1-hour basis, with break times supported down to a granularity of 15 minute intervals.

The Simulator evaluates the performance of deployment plans against test incidents. The simulation handles test incidents in chronological order. The behaviour of each agent is modelled according to the individual deployment determined by the shift plan. When an incident occurs, the available agent with the shortest response time is dispatched without reference to future incidents. Success is defined as the agent arriving within the target time for the incident priority.

System Implementation

The GRAND-VISION system is implemented in Python based on the Django framework for database integration, and linked to a web-based frontend app. A central backend server process handles requests received from the frontend. A planning worker process polls the database for pending deployment tasks, and when a task is detected, it takes the incidents generated by the Incident Generator, which is a separate dedicated Flask app running TensorFlow. The predicted travel time from one location to another is provided by another dedicated service which is linked to a travel time prediction model not described in this demo. By adopting this modular service structure, new methods, such as enhanced incident prediction or travel time prediction, or legacy methods, can be easily integrated for experimentation and future system extension. The Optimizer and Scheduler use the Python API of the IBM CPLEX solver.

There are two types of users - Commander and Analyst. The Commander uses the system to generate and view daily deployment plans for their own area of responsibility only. They have access to a streamlined interface that focuses on easy plan creation that is suitable for a non-technical user. The Analyst role is intended for technical users and has access to all the system features. These include the ability to generate deployment plans for all geographic areas under the agency, tune parameters such as the number of training scenarios for the Optimizer, and select which of the available methods is used for each module. This last feature allows the Analyst to evaluate the potential performance of new methods against the default, without interfering with the Commander's daily work. The Analyst can also perform other unique functions, such as uploading incident data for visualization, carrying out plan validation, and updating the prediction model used by the Incident Generator.

Development and Trial Experience

We present some challenges and learning points from working directly with our partner agency. Firstly and topically, the COVID-19 pandemic has presented difficulties, both in physically meeting with the client, and in executing the field trial, as the agency was not inclined to introduce experimental plans during such a disruptive time. However, it also allows us to investigate the influences of a pandemic on emergency incident behaviour, as the incident prediction model is based on pre-virus data. We will use the trial to assess its accuracy under unprecedented conditions.

Secondly, when developing solutions, there are a number of operational considerations to accommodate. At an early stage of the project, we considered altering the shifts, but the agency was concerned about the level of disruption to their logistics and their patrol agents, who structure their lives around the current shift pattern. This was a common refrain during the project development, as ideas had to be evaluated not just for their research merit, but for their operational feasibility and the ability to 'sell' the ideas to the commanders who are concerned with staff morale.

Thirdly, working with the agency from the start provided valuable insights into what factors must be specifically tailored compared to other use cases. Each LEA is different, and the system usability and functionality could be developed in line with the experience of the agents who would have to use it. In a real world problem, it is sometimes necessary to recognise the limitations of automated planning and scheduling, and know how to leave room for expert knowledge (such as through provision for pre-allocations).

These challenges notwithstanding, the GV system has undergone extensive User Acceptance Testing (UAT) with our partner agency and is ready for field trials.

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References

Chase, J. 2021. GRAND-VISION: An Intelligent System for Optimized Deployment Scheduling of Law Enforcement Agents. URL https://youtu.be/jsxGKxXSeNs.

Chase, J.; Phong, T.; Long, K.; Le, T.; and Lau, H. C. 2021. GRAND-VISION: An Intelligent System for Optimized Deployment Scheduling of Law Enforcement Agents. In *Proceedings of the 31st International Conference on Automated Planning and Scheduling (ICAPS)*, to appear. AAAI Press.