Dynamic Allocation of Emergency Resources

CS221 Project Proposal

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***Abstract*—By dynamically allocating resources such as personnel and vehicles in emergency situations, we can provide a solution that minimizes damage and loss of life while also conserving taxpayer dollars.**

Keywords—public safety; emergency events; reinforcement; MDP; resource allocation; time series

I. Motivation

Each year, emergency responders assist in millions of critical events across the country. The size of an emergency response can scale from a single paramedic to multi-state crews fighting large fires. As emergency events, the time it takes first responders to arrive on scene is critical, with minutes often making the difference between life and death. Because of these factors, standard staffing and resource use is very high to make sure enough responders are available at any given time. These factors make emergency response an important potential application for optimizations. Thus, a model that makes dynamic decisions on allocation of resources would be extremely useful to government and department management in day to day operation.

II. Approach

A. Goals and Scope

Our goal is to use historic per day emergency incidents in a specific geographic region as an input for our model. We will frame this application as a reinforcement learning problem where training examples will be days of historic data drawn from the pool of emergency events for the region as well as potential relevant weather, geographic, structural, and demographic features that may be added if our simple data source is found lacking. This will allow our model to make an optimal allocation of resources over our region of interest at any given time.

The particular region of interest that will be explored is the city of San Diego. Specifically, we will be allocating fire trucks for the San Diego Fire Department. Our model is time sensitive and will be evaluated at time steps covering a 24 hour time period. Our model will be fed a transcript of incidents over a day as its input (fed at the corresponding time step), and will output the locations that the fire trucks have moved to at each time step. We will measure model performance by simulating our model over a test set of randomly selected days, and returning the average response time per incident. Models can then be compared on the basis of their average response time. Response time will be calculated as the minimum distance between an available fire truck and an incident multiplied by a basic speed of 40 mph.

A concrete example input for a timestep would be the following:

[FIRE, Vehicle Fire Freeway,
2016-08-18T23:51:56, (32.839, -117.144)]

And the output for the timestep would be a dictionary with a fire truck number as a key and a location destination (for the following timestep) as an output. E.g. for one timestep with 2 trucks:

{truck1: (32.839, -117.144), truck2: (32.822, -116.909)}

This input, output behavior mirrors that of a real life decision-maker where incidents are reported and directives are given. Our different model implementations will be compared via response time (the difference in time from when an incident is announced and when a vehicle arrives on the scene). This is an important real world metric, and given our formulation, can be calculated based on input and outputs allowing us to compare models.

B. Data Sources (concrete data example)

Our source of historic emergency incidents is the San Diego Open Data Portal which provides every fire incident responded to in the last year. This dataset is comprised of the type, location, date and time, and category of severity for approximately 150,000 incidents [2]. Historic fire data will possibly be supplemented with weather [3], geographic [4], and demographic data [5] corresponding to the region of interest if needed.

C. Model and Topics

A perfect approach, or oracle, would result from having all of the important knowledge of all future emergency incidents. Thus, this oracle would route trucks so that for any incident a truck is already present and available. A baseline approach would result from knowing nothing about future incidents nor making active routing decisions. This approach would for any given incident simply route a random truck to the incident and nothing more.

After implementing the two approaches, we found that (depending on initial assumptions), the baseline had a quite high total error, whereas the oracle was very close to zero. This difference is exactly what we expected. The oracle knew where the incident would be taking place and was able to route fire trucks there before the incident actually happened. Therefore, there was always a truck ready to respond exactly where it was needed and when it was needed. On the other hand, the baseline approach had the trucks blindly wander around the city until there was an incident. Even the closest truck was usually far from the incident. Our solution will lie somewhere between these extremes.

Our approach to a solution is to utilize reinforcement learning to learn in the uncertainty of not knowing when and where future incidents will occur. We see a potential to model the situation as a MDP. In particular, there is a probability that for any (state, action) that represents (fire truck and incident locations, firetruck directive) the next state will contain a new incident location.

D. Challenges

One of our primary challenges will be identifying a good feature extractor for our reinforcement learning model. Since the state space of our MDP is extremely large, it will be necessary for our feature extractor to allow our reinforcement learning algorithm to generalize well.

E. Similar Applications

A similar application of machine learning to help emergency responders was done by Bayes Impact. They analyzed Seattle police report data in order to determine ways in which Seattle could better deploy officers with the goal of minimizing serious and violent crime [6].

F. Source Code

Source code for our project can be found at https://github.com/tyler-romero/fire-prediction.

References

[1] Haynes, Hylton JG. "Fire loss in the United States during 2015." National Fire Protection Association. Fire Analysis and Research Division, 2016.

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[4] *SanGIS*. San Diego Geographic Information Source, n.d. Web. 21 Oct. 2016.

[5] "San Diego Demographic Data." *Census.gov*. N.p., n.d. Web. 21 Oct. 2016.

[6] Wong, Jeff. "Walking the Beat: Mining Seattle's Police Report Data." *Bayes Impact*. N.p., n.d. Web. 21 Oct. 2016.