Dynamic Allocation of Emergency Resources

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CS221 Final Project Poster

Motivation

Emergency services respond to millions of calls every year throughout the city of San Diego

- Minutes/seconds in response time difference between life/death
- High base cost from high static staffing
- Simple station staffing model
- Maximum average response time

Figure 1: Burning building

Save lives by decreasing response time through effective routing and allocation of resources.

Data

- 8 years of emergency incident data from the city of San Diego
- Cleaned, and converted in latitude and longitude

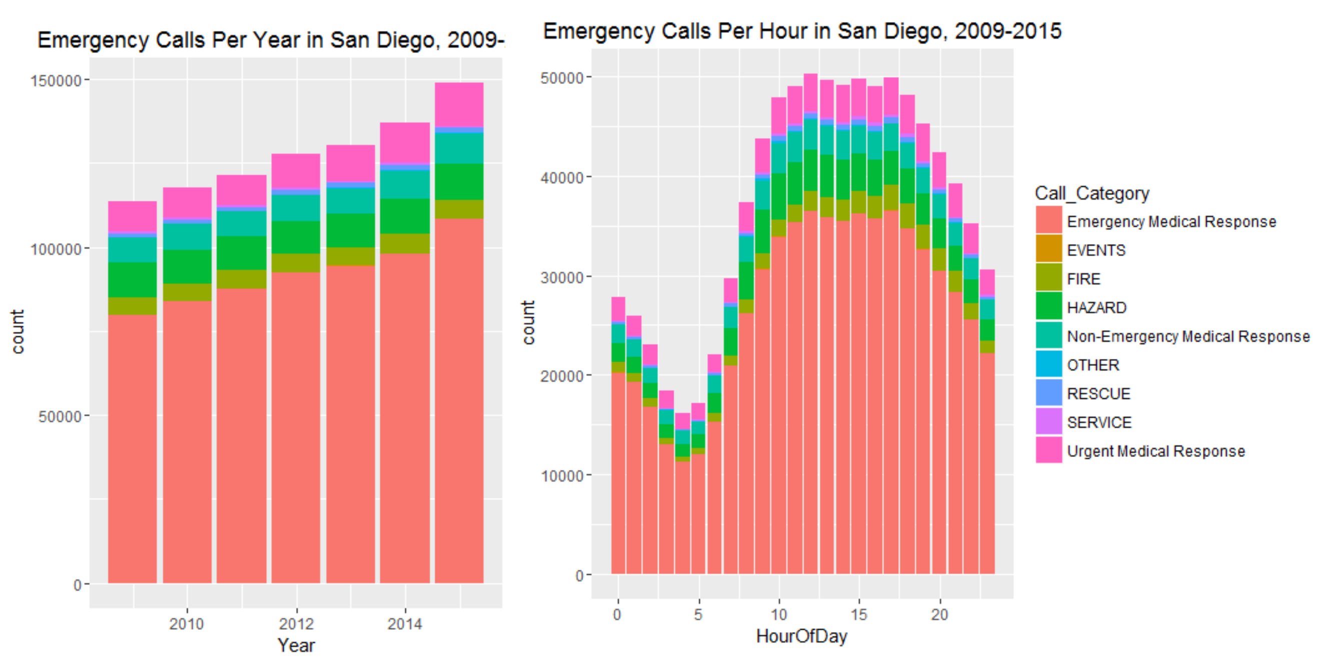
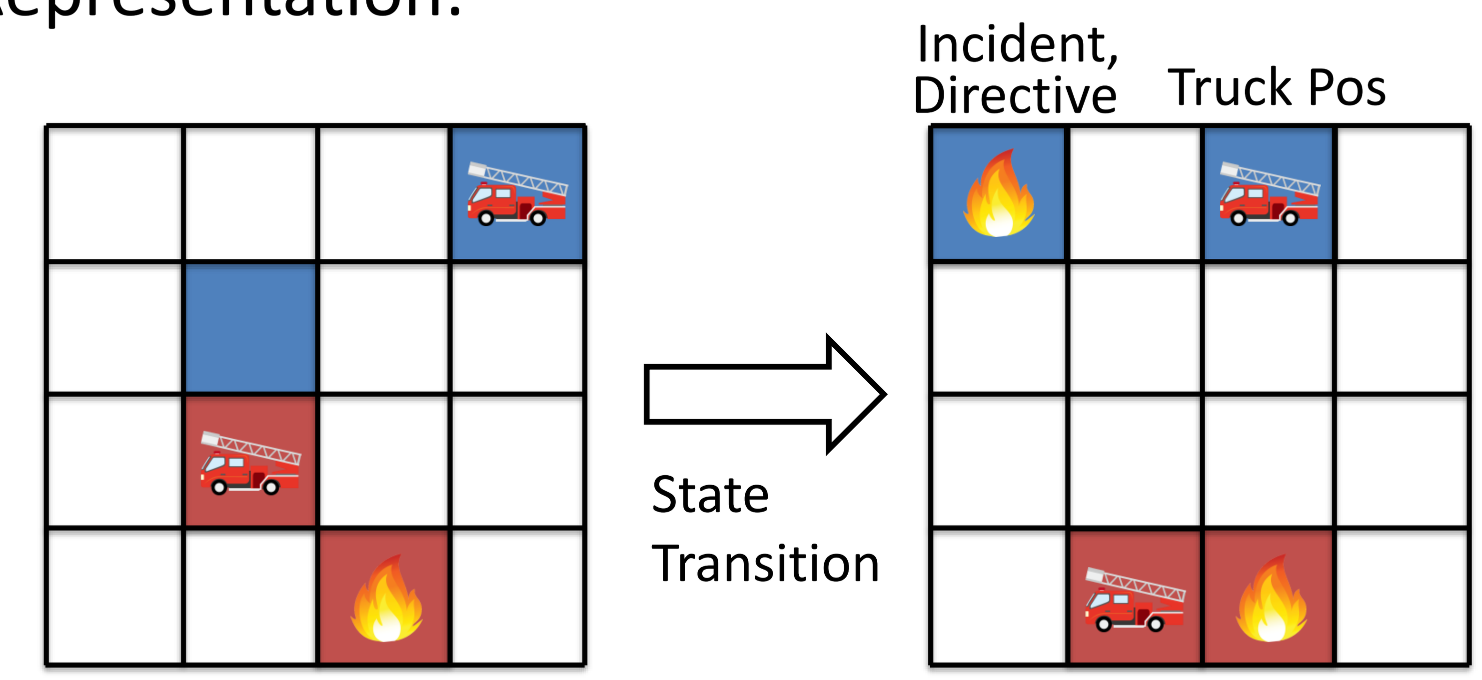


Figure 2: Data

Temporal-spatial correlation but unknown underlying dynamics.

Models

State Representation:



- A state is comprised of a **grid**, a list of **truck positions**, and a list of **current incidents**.
- An action is an **assignment** of each truck to a destination.

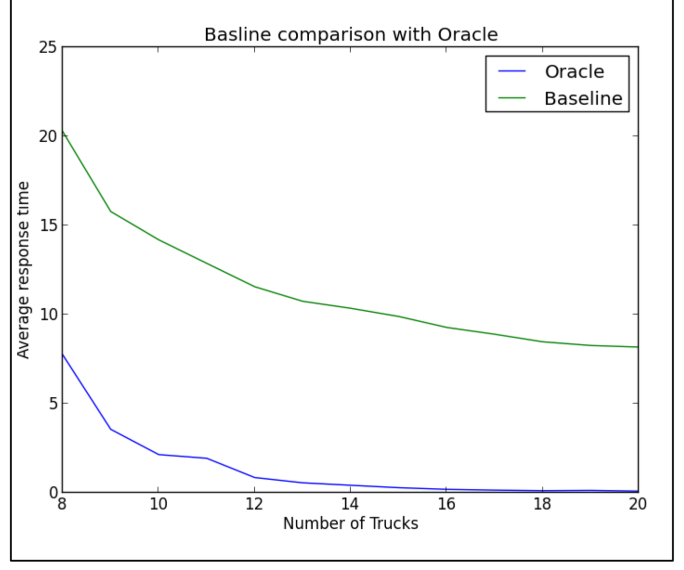
Baseline & Oracle:

Baseline:

- Random exploration
- Greedy assignment to current incidents

Oracle:

- Greedy assignment to future incidents



Greedy-Q Learning:

- Random initial positions
- Actions
  - Sampled state space
  - Greedy assignment
- Feature Extraction
  - Distance between trucks
  - Distance between truck and incident
- Reward Function
  - Inv. distance to incident

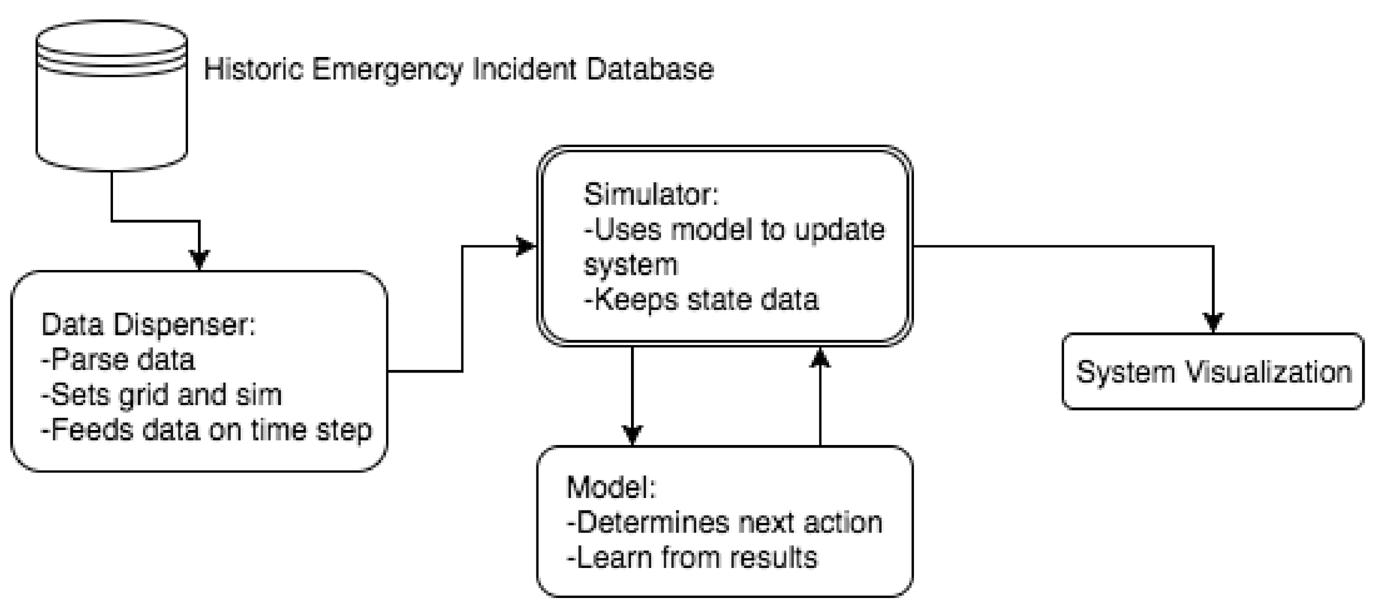
Cost Constraint:

- Random initial positions
- Actions
  - Add/remove trucks
- Feature Extraction
  - Time of day
  - Current allotment
- Reward Function
  - Inv. distance to incident
  - Inv. Cost

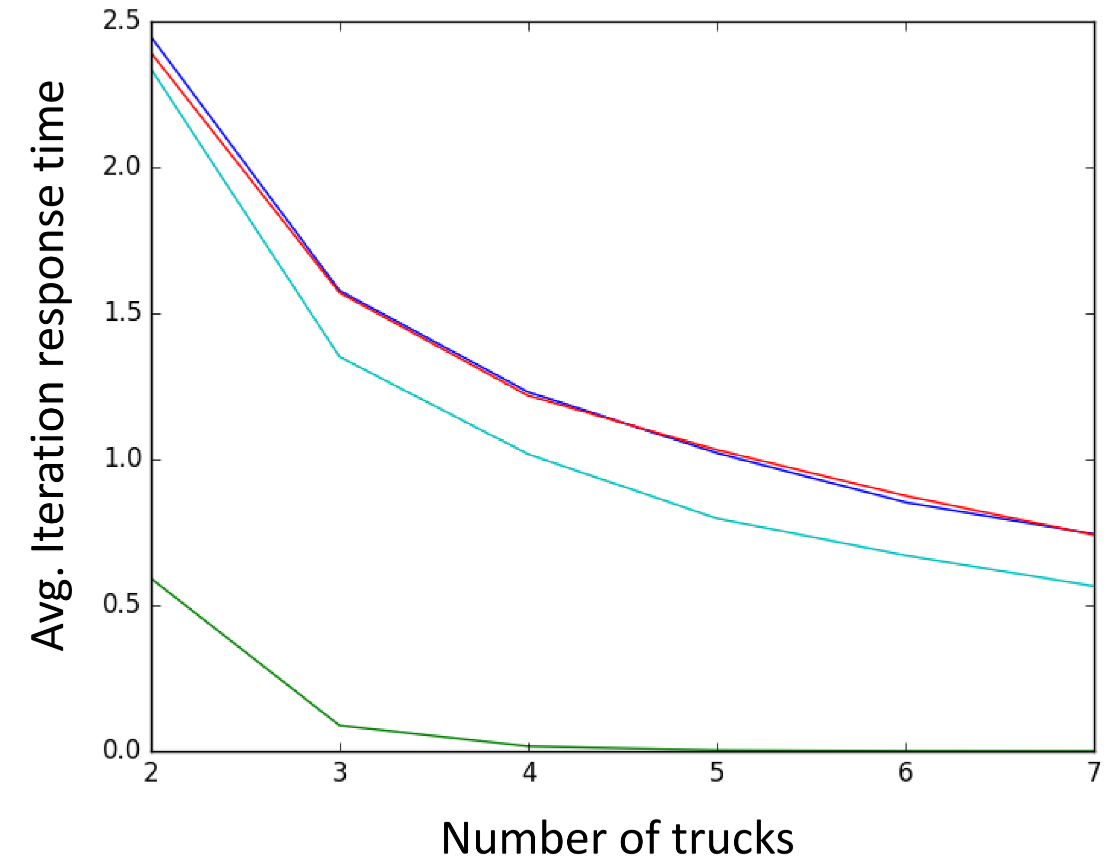
In Progress

Implementation

- Pull from historic data
- Generate grid representation of location
- Feed incidents based on simulation time



Results



- Comparison of green oracle, blue q-learning greedy model, and red baseline

	Baseline Model:	Greedy-Q Learning Model:
Response Time	1.53 iterations	1.34 iterations

Discussion

- Difficulty handling large state space
  - Sampled space for reduction
- Feature selection issues in statistical sharing
- Need to capture temporal patterns
- Potential: region specific strained models
- Potential: Joint problem with constraint of maximum cost

Learn actions in large state space with heavy sampling and feature sharing

Learn patters from divisions and constraints

References

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

[2] San Diego Open Data Portal. The City of San Diego, n.d. Web. 21 Oct. 2016.