Predicting Emergency Incidents in San Diego

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CS229 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
- The ability to effectively predict where emergency incidents will occur could save both lives and money

Figure 1: Burning building

Our goal is to create a model that can effectively predict where incidents are likely to occur over the next several hours.

Data

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

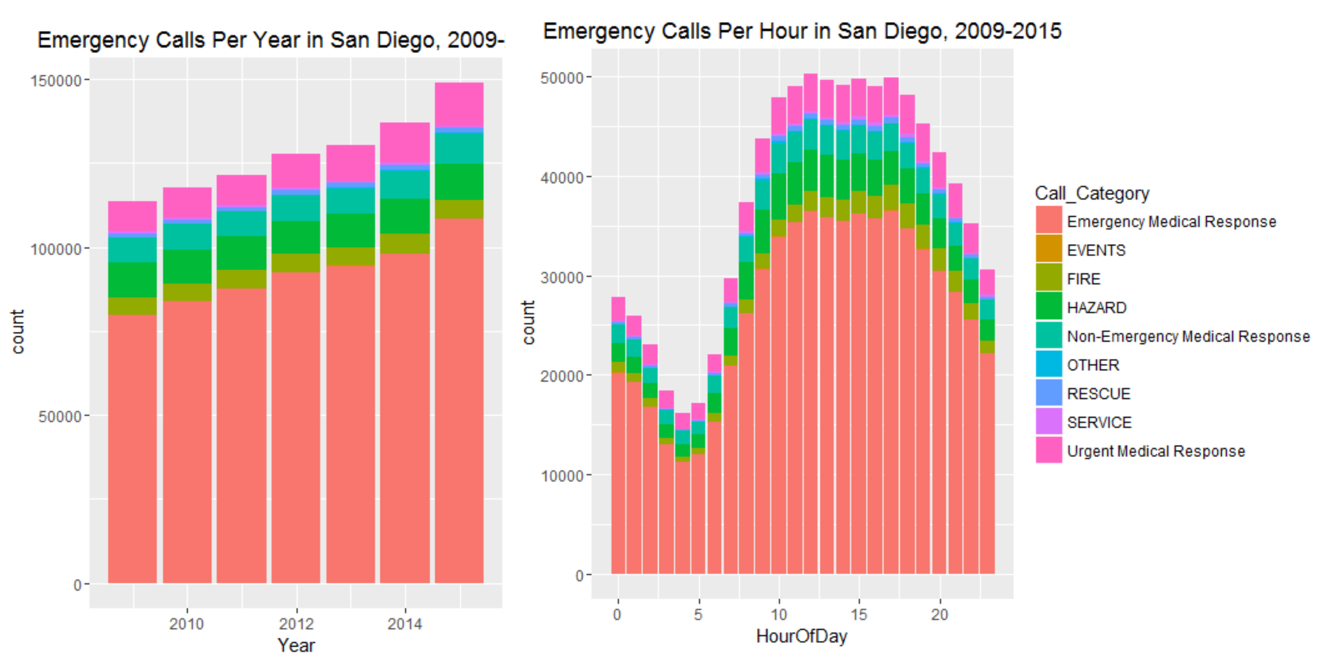


Figure 2: Data

Temporal-spatial correlation but unknown underlying dynamics.

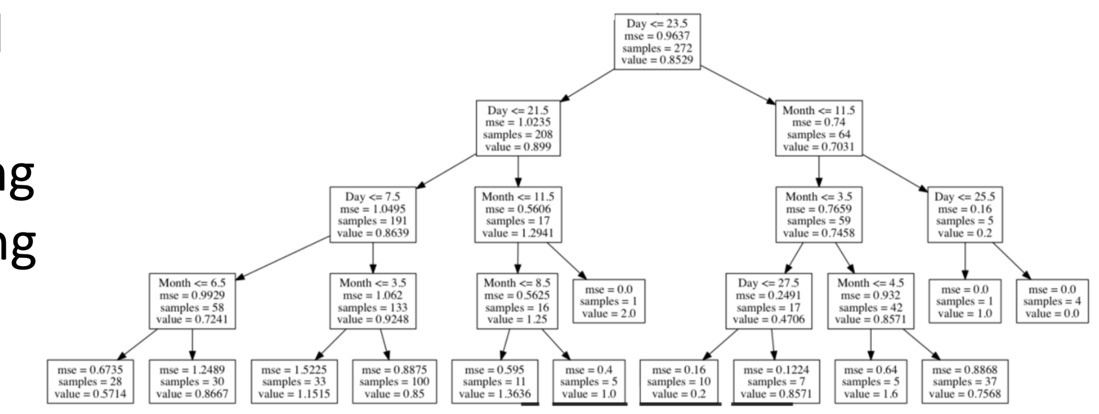
Problem Descriptions

- Generate grid representation of San Diego
- Problem 1:
  - Predict the number of incidents that will happen per day in each grid cell
  - Helpful for staffing decisions
- Problem 2:
  - Identify which exact areas of San Diego are the most high-risk on a specific day
  - Helpful for emergency anticipation

Models

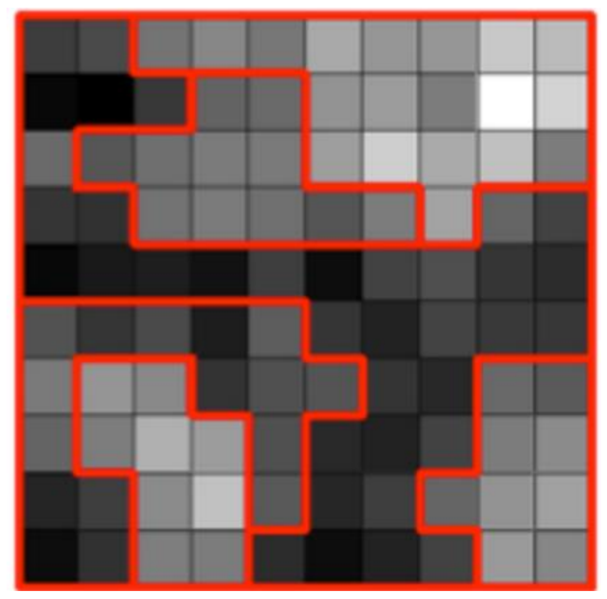
Decision Tree Regression:

- Used month, day, hour, and grid location as covariates
- Effective, but prone to overfitting
- Non-representative of underlying distribution
- Uses categorical data well



Spatial Clustering:

- Identify locations that are both contiguous and similar in nature based
- Use these clusters in order to build better-informed models
- Steps:
  - Generate a model for each cluster
  - Evaluate and update model on cluster
  - Re-cluster based on model performance



Example spatial clustering

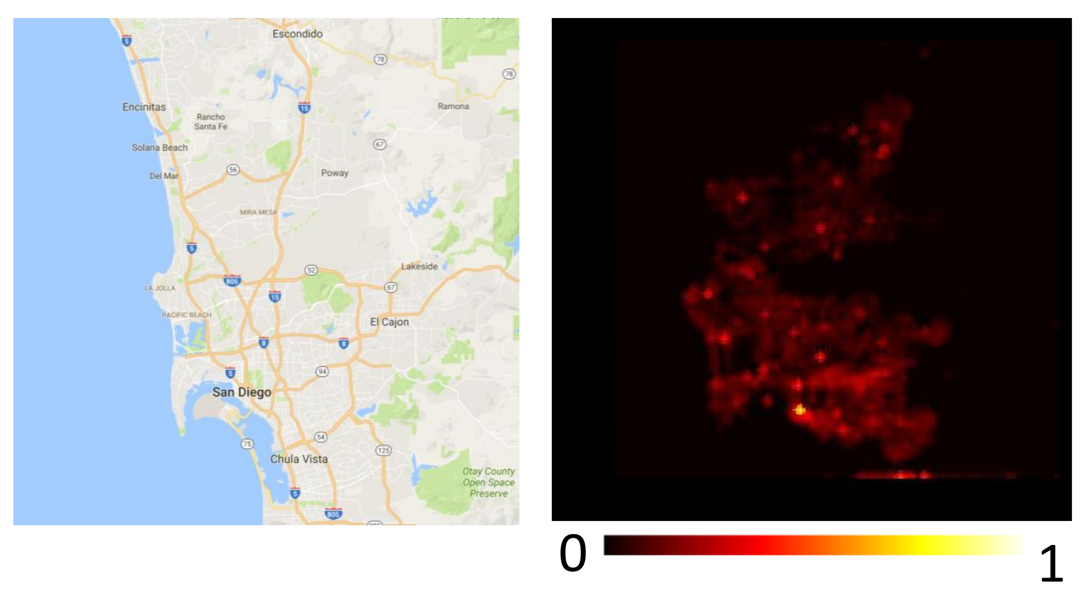
Spatial-Temporal Prospective Excitation Model:

- Utilize temporal and spatial difference in determining likelihood at each locations

$$p(x', y' | D, t; \theta) = \sum_{D_t} G(x', y', D_t | \theta)$$

- Choose top x% of points that capture Y% of events in a day.

Example likelihood for given day



Results

Problem 1:

- Tested our models using 10-fold cross validation

Experimental Model:	RMSE:
Decision Tree Regression	0.7010 (incidents/hour)
Decision Tree Regression with Max Depth 10	0.4827 (incidents/hour)
Spatial Clustering with linear regression	0.4583 (incidents/hour)

Problem 2:

- Tested our model on ten randomly selected days
- Trained model on the weeks leading up to each of those days
- Model selects the top 1% of at-risk locations

Average Proportion of Daily Incidents Captured:
0.338

Example of selections for a given day:

Discussion

- Small variation and little information returned by solutions to problem 1 leads to the need for a solution to problem 2
- Temporal fluctuations are important, but difficult to anticipate
- Our solution to problem 2 would could effectively inform a dynamic resource allocation model
- Next Steps:
  - Model each type of incident separately
  - Predict type of incident as well

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.