Emergency Medical Services Demand Forecasting: A Survey of Machine Learning Methods

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Introduction

Emergency medical services (EMS), commonly referred to as ambulance, paramedic or prehospital emergency services, are a critical component in the delivery of urgent medical care to communities. The primary goal of EMS agencies is to minimize their response time to individual call requests, and in doing so, minimize the rate of mortality and morbidity [1]. By their very nature, EMS systems are extraordinarily complex. The demand for ambulances is dynamic and is known to fluctuate spatially and temporally based on the time of day and day of the week [2].

Related research has sought to identify more sophisticated call forecasting approaches to improve the predictive models used for demand planning. However, many of these studies have focused on developing forecasts for broader time periods and geographic areas. While these types of forecasts are valuable for strategic and tactical capacity planning over longer periods of time (i.e. monthly or yearly), they are not very useful for short-term operational decisions, such as daily and hourly deployments. Furthermore few researchers have performed investigations that explore the application of machine learning algorithms to predict EMS call demand.

Objective

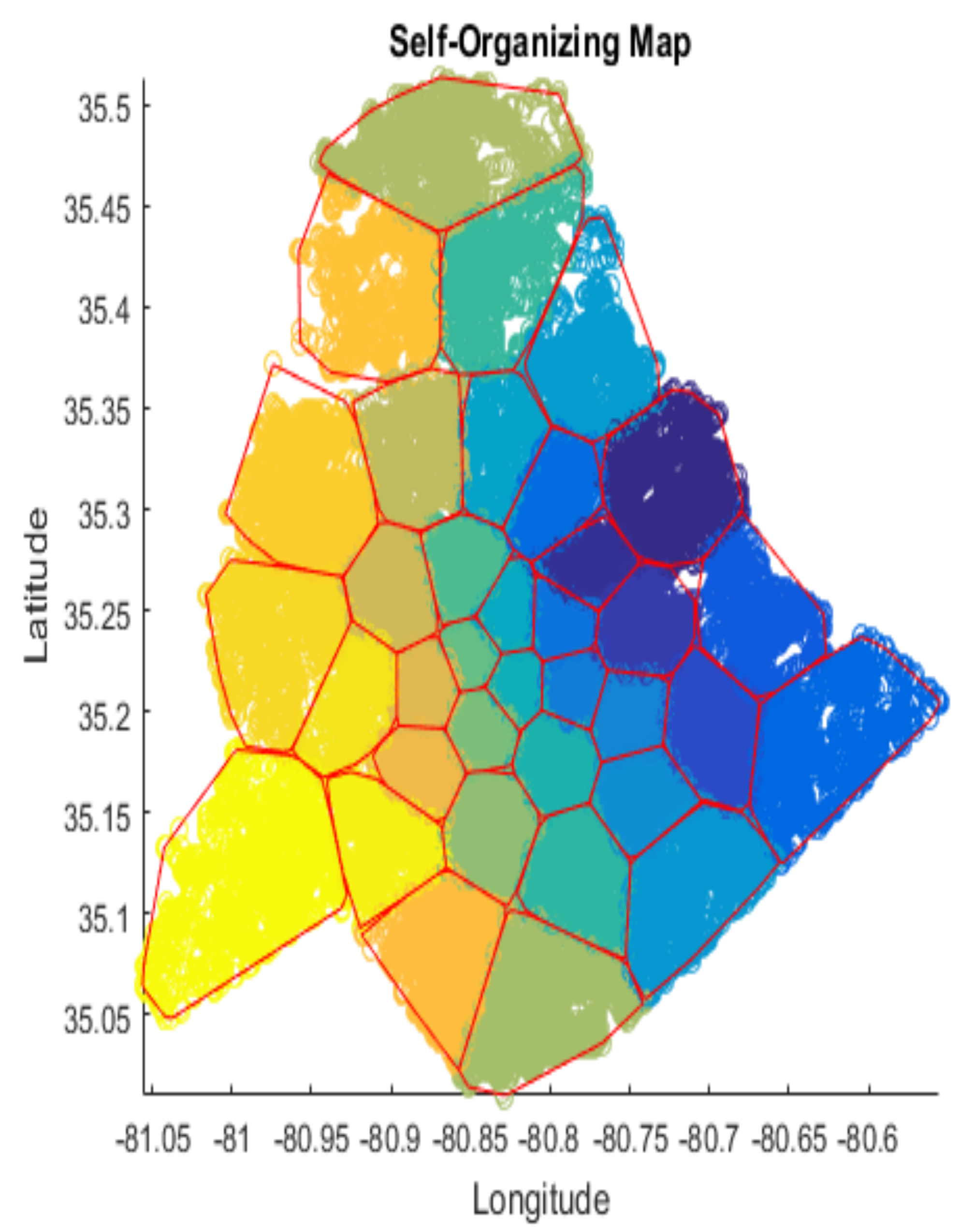
The focus of this study will be to produce call demand forecasts at various scales of time and space using a survey of different supervised machine learning algorithms. Our primary objective is to conduct an exhaustive study, comparing the performance of various algorithms ability to predict future demand for emergency medical services.

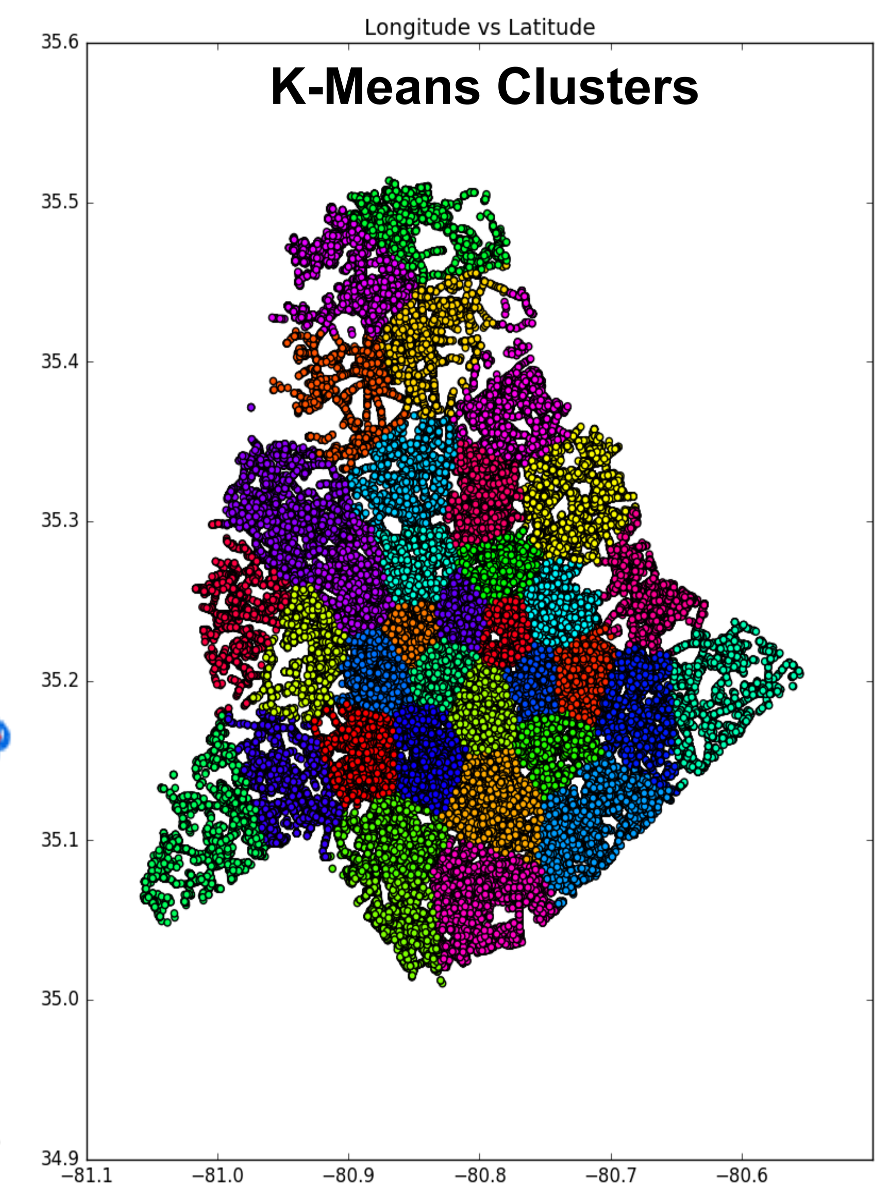
Methods

We began our analysis by implementing an Artificial Neural Network, based on a prominent paper in the EMS field as our base model. Preparing our data for analysis we applied a novel approach to aggregating call records into different geographic clusters using K-Means clustering and a Self-Organizing Map. To generate call volume predictions various machine learning algorithms were analyzed using different selections of training features and sample distributions. The following supervised learning models were implemented:

- Neural Networks
- Naïve Bayes
- Support Vector Machines
- K-Nearest Neighbor
- Decision Trees with AdaBoost

Results





Key Performance Metrics

- **F-Score**

Precision = True Positive / (True Positive + False Positive)

Recall = True Positive / (True Positive + False Negative)

*F-Score = 2 * (Precision * Recall) / (Precision + Recall)*

- **Accuracy**

Correct Predictions / Total Predictions

Supervised Learning Model	Clustering Approach	F-score "label 0"	F-score "label 1"	F-score "label-2"	F-score "label-3"	F-score "label-4"	F-score	Accuracy
Neural Network (1)	K-Means	0.87	0.07	0	0	0	0.67	76%
Neural Network (2)	K-Means	0.86	0	0	0	0	0.65	75%
Naïve Bayes (1)	SOM	0.84	0.024	0.0004	0.0	0.0	63.9	73.89%
Naïve Bayes (2)	K-Means	0.80	0.173	0.053	0.003	0.0	63.86	67.42%
AdaBoost (1)	K-Means	0.88	0.07	0.07	0.08	0.37	0.69	77%
AdaBoost (2)	K-Means	0.66	0.25	0.16	0.45	0.98	0.57	52%
AdaBoost (3)	K-Means	0.69	0.25	0.17	0.45	0.99	0.59	54%
SVM (1)	SOM	0.86	0.13	0.021	0.038	-	0.75	75.14
SVM (2)	SOM	0.83	0.21	0.06	0.12	-	0.72	72%
KNN (1)	SOM	0.80	0.20	0.06	0.07	-	0.67	66.7%
KNN (2)	SOM	0.85	0.16	0.008	0.002	-	0.74	74.1%

After implementing a collection of different supervised learning models to predict EMS call volumes, we found that our Support Vector Machine implementation performed the best with an overall higher accuracy and superior individual class accuracy distribution. More specifically, the top performing SVM yielded an overall accuracy of 75%, a F-Score of 86%, a RMSE of 42.8% and a MAPE of 20.9%. While other models came close, or surpassed, many of these metrics at an individual level none performed better overall than SVM. One of the most interesting conclusion we had with SVM was that using data for a single month, versus multiple months, produced a more generalized model. Additionally, while inserting zero volume call records contributed more to our problem of class imbalance we found that it is necessary to provide an accurate representation of the data. For instance, running our SVMs without zero volume call records resulted in models that always predicted '1' for all sets of input features. One limitation of SVM we encountered was the runtime required to process larger datasets.

Ideally, additional time and resources would have contributed to richer results and the ability to test more scenarios and strategies. Suggestions for future research include, working with larger datasets representing more recent time periods, incorporating additional features such as call disposition and demographics, as well as applying various under and over sampling techniques to correct the inherit class imbalance.

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