Spatial Temporal Resource Demand Model for Emergency Response Management

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https://statresp.ai

Introduction

- Annually, road accidents account for 1.25 million deaths globally and about 240 million EMS calls are made in the U.S.

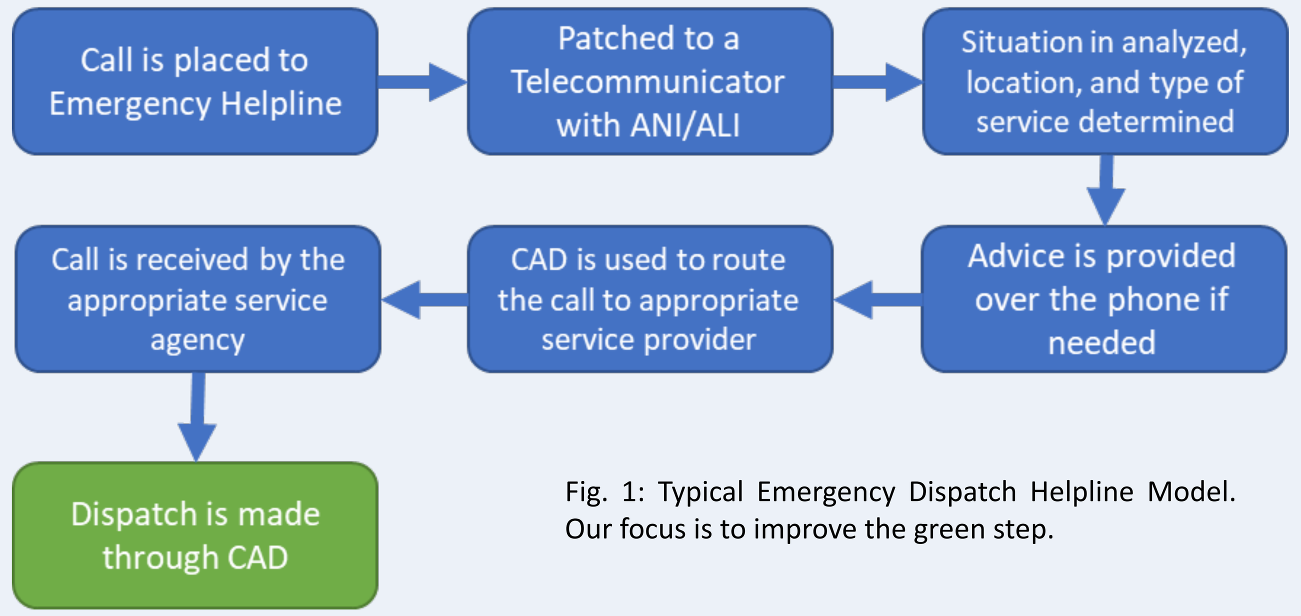


Fig. 1: Typical Emergency Dispatch Helpline Model. Our focus is to improve the green step.

- We focus on the Interstate Highway network of the state of TN. Among the yellow segments only 20% of them accounts for 80% of the accident, and we use them for our prediction model.

Fig. 3: Blue lines represent TN's roadway network. Yellow segments represent interstate highway segments under the jurisdiction of TDOT, and red vehicles show the potential locations of responders.

- Although frequency of road accidents is high, when viewed from the perspective of total time and space, incidents are rare events. Sparsity > 99.8%.

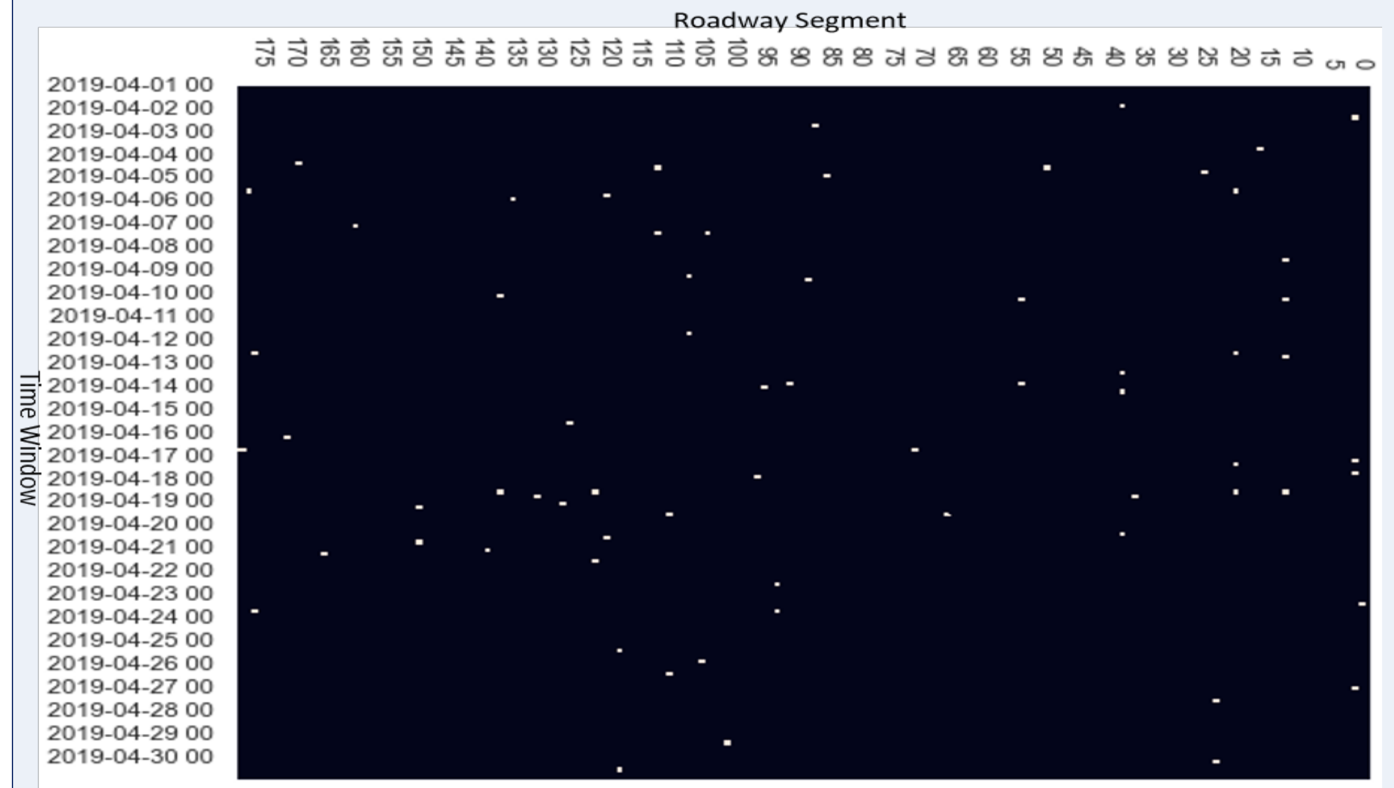


Fig. 2: randomly selected 180 road segments for 4-hour time windows in April 2019. Each pixel in the matrix denotes the presence (white) or absence (black) of an accident

Data

Dataset	Range	Size	Rows	Features	Source	Frequency	Type	Description
-	-	-	-	Time of day	derived	-	Temporal	We divide each day into six 4-hour time windows.
-	-	-	-	Weekend	derived	-	temporal	A binary feature that denotes weekdays.
Incident	02/01/2017 to 05/01/2020	21MB	80,000	Past Incidents in the last window	derived	-	Spatio-temporal	Number of incidents on the segment in the last time window of 4 hours
				Past Incidents in a day	derived	-	Spatio-temporal	Number of incidents on the segment in the last day
				Past Incidents in a week	derived	-	Spatio-temporal	Number of incidents on the segment in the last week
				Past Incidents in a month	derived	-	Spatio-temporal	Number of incidents on the segment in the last month
Weather	02/01/2017 to 06/01/2020	300MB	1,400,000	Visibility	Weatherbit	1 hour	Spatio-temporal	A measure of the distance at which an object or light can be clearly discerned.
				Wind Speed	Weatherbit	1 hour	Spatio-temporal	Speed of wind.
				Precipitation	Weatherbit	1 hour	Spatio-temporal	Amount of precipitation.
				Temperature	Weatherbit	1 hour	Spatio-temporal	It is the reported temperature.
Traffic	04/01/2017 to 12/01/2020	1.2TB	30,000,000,000	Congestion	derived	5 minutes	Spatio-temporal	Congestion is the ratio of the difference between free flow speed and the current speed to free flow speed
				Free Flow Speed	INRIX	5 minutes	spatial	The speed at which drivers feel comfortable if there is no traffic and adverse weather condition.
				Traffic Confidence	INRIX	5 minutes	Spatio-temporal	A confidence score regarding the accuracy of the traffic data (we collect this directly from INRIX).
Roadways	Static	81MB	80,000	Lanes	INRIX	static	Spatial	Number of lanes for a roadway segment.
				Miles	derived	static	Spatial	Length of a roadway segment.
				iSF	derived	static	Spatial	Inverse scale factor which represents the the curvature of a roadway segment.

Spatial Temporal Prediction

The goal is designing a function, $f\ (X \mid w, \theta)$, where X represents a measure of incident occurrence such as a count or presence of incidents during a specific time period. θ represents the parameters regarding the model.

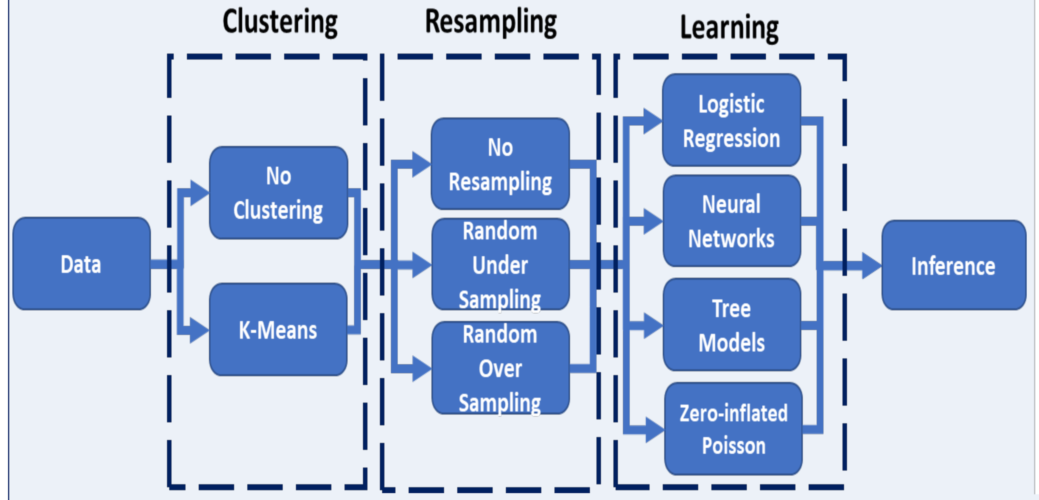


Fig. 4: Schematic pipeline of the forecasting model

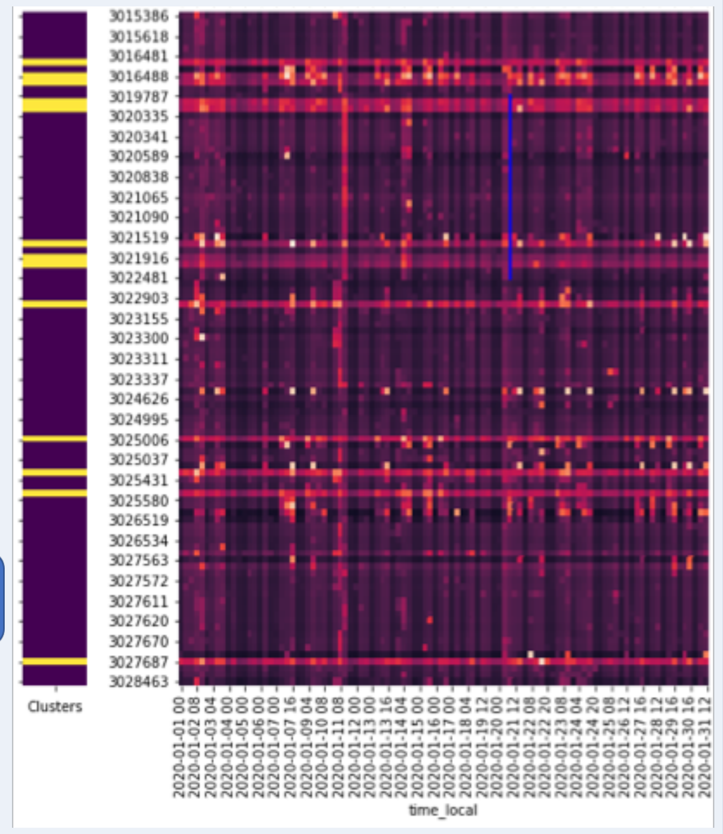
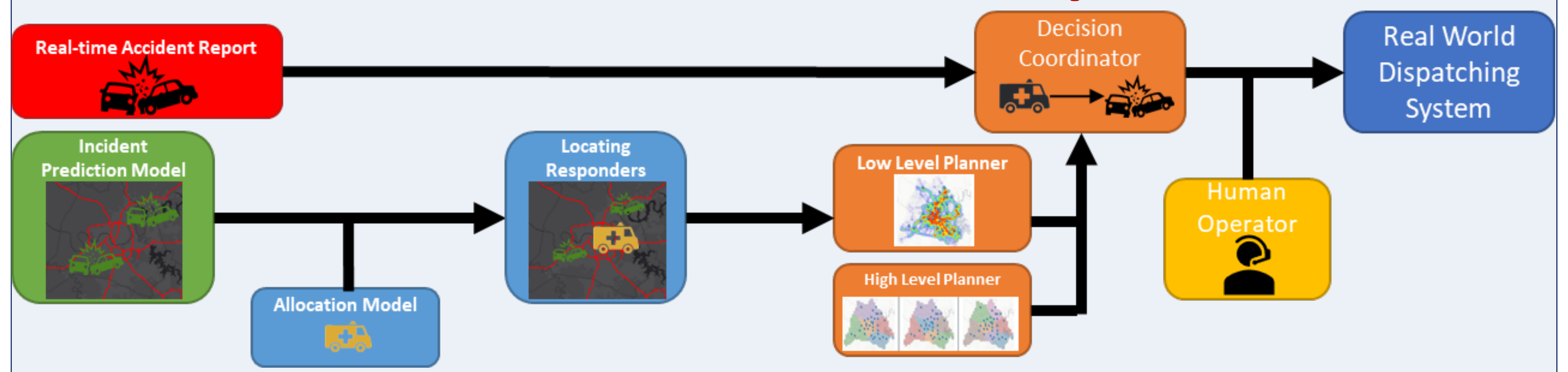
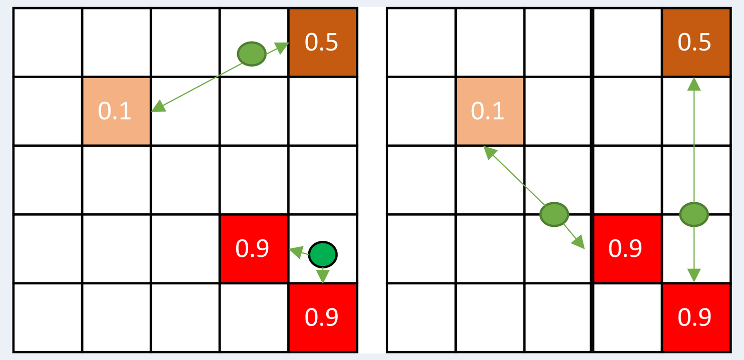


Fig. 5: prediction results using 2 clusters.

Prediction to Inform Response



- We modify the p-median optimization problem by adding a *balancing term* that accounts for increased load on responders in hotspots.
- *The balancing term* has a parameter called α. As it increases responders (green dots) are tightly packed around high demand areas (red).



$\alpha = 0$ $\alpha > 0$

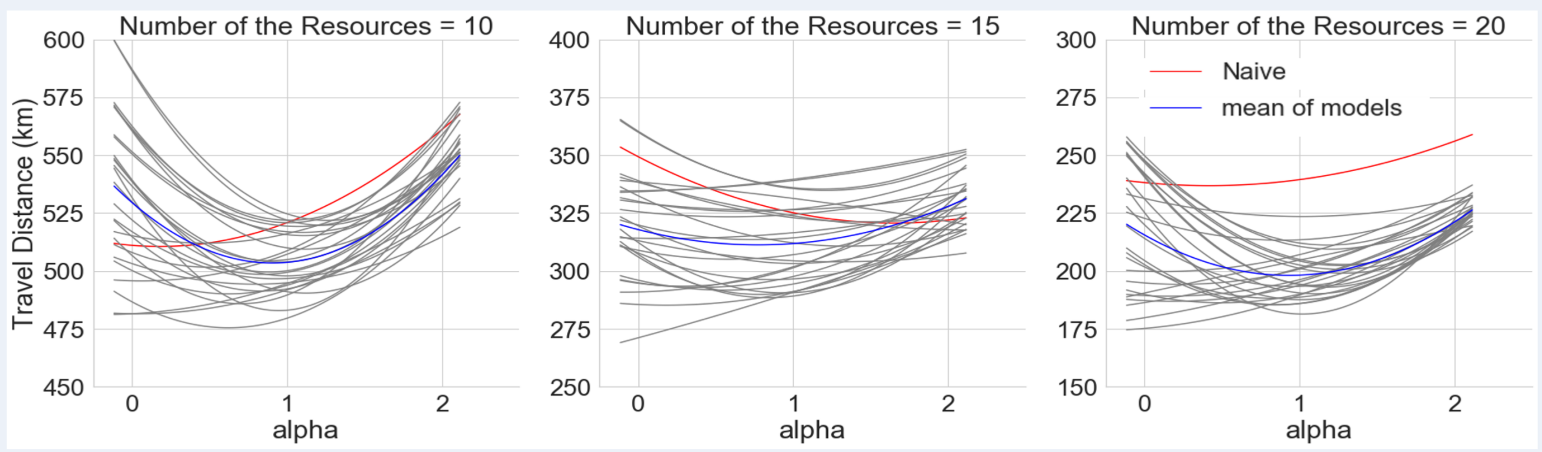
Results

- Different modeling paradigm (Logistic regression, neural network, random forest, Zero inflated Poisson) and parameters (α – concentration and p - # responders) were explored. Existing work use hotspot analysis which fails in such sparse datasets.

			Classification Metrics				Correl-ation		Total travel distance of responders per accident (km)												Average number of unattended accidents								Maximum number of unattended accidents							
									p=10				p=15				p=20				10				15				10				15			
Model	**Clustering**	**Resampling**	**Acc.**	**Prec.**	**Rec.**	**F1**	**Pear.**	**Spear.**	α=0	α=0.5	α=1	α=2	α=0	α=0.5	α=1	α=2	α=0	α=0.5	α=1	α=2	0	0.5	1	2	0	0.5	1	2	0	0.5	1	2	0	0.5	1	2
Naive			**95.5**	3.8	4.2	4.0	**82.1**	60.8	39.48	38.44	43.21	45.35	26.29	25.78	27.34	26.78	19.29	19.43	20.36	23.12	0.54	0.49	0.48	0.46	0.02	0.01	0.01	0.01	15.00	14.00	14.00	16.00	2.00	1.00	1.00	2.00
LR	No cluster	No resampling	94.0	13.8	27.4	18.2	70.4	55.2	41.54	41.88	40.04	44.90	25.30	25.16	26.93	26.73	18.98	16.78	17.41	20.23	0.54	0.47	0.42	0.42	0.00	0.00	0.01	0.01	16.00	13.00	14.00	12.00	0.00	0.00	1.00	1.00
		RUS	93.0	12.8	32.3	18.3	63.1	54.7	42.90	43.41	39.97	44.36	25.07	25.38	26.01	26.94	19.07	18.05	17.00	20.41	0.56	0.52	0.46	0.46	0.00	0.00	0.01	0.00	17.00	17.00	15.00	15.00	0.00	0.00	1.00	0.00
		ROS	93.0	12.8	32.3	18.3	63.2	54.7	42.83	43.90	39.80	44.74	25.14	25.33	25.88	27.22	19.02	18.25	16.61	20.06	0.56	0.51	0.46	0.45	0.00	0.00	0.01	0.00	17.00	17.00	15.00	14.00	0.00	0.00	1.00	0.00
	clustering	No sample	93.0	12.5	30.9	17.7	76.6	58.4	40.79	39.44	42.57	44.81	24.44	25.14	26.21	27.79	18.55	19.39	18.95	21.45	0.53	0.41	0.43	0.44	0.02	0.01	0.01	0.01	17.00	12.00	13.00	15.00	3.00	1.00	1.00	2.00
		RUS	92.3	12.1	**34.4**	17.8	74.2	58.1	42.69	40.96	42.16	43.75	24.66	24.75	26.20	27.78	18.93	18.69	17.18	20.08	0.54	0.48	0.42	0.40	0.01	0.00	0.00	0.01	15.00	15.00	11.00	12.00	1.00	0.00	0.00	1.00
		ROS	92.4	12.2	34.2	17.9	74.2	58.1	42.78	40.89	42.71	44.22	24.58	24.84	26.18	28.29	18.87	18.66	17.04	19.90	0.54	0.48	0.42	0.41	0.01	0.00	0.00	0.01	15.00	15.00	11.00	15.00	1.00	0.00	0.00	1.00
NN	No cluster	No resampling	94.9	19.2	32.8	24.0	71.7	58.5	37.04	39.12	39.21	43.13	22.35	23.57	24.74	26.69	15.70	16.44	17.52	20.33	0.45	0.40	0.43	0.40	0.01	0.00	0.01	0.01	12.00	11.00	11.00	11.00	1.00	0.00	1.00	1.00
		RUS	95.0	19.2	32.6	24.1	73.2	59.3	37.44	39.07	37.83	43.84	22.24	23.85	24.97	27.64	16.40	16.21	17.05	20.27	0.47	0.41	0.43	0.45	0.00	0.01	0.01	0.01	12.00	11.00	11.00	12.00	0.00	1.00	1.00	1.00
		ROS	94.9	19.1	32.8	23.9	69.3	54.7	37.32	37.71	39.86	43.21	21.57	23.15	24.32	26.61	15.70	15.81	17.23	20.33	0.46	0.41	0.42	0.43	0.00	0.00	0.00	0.01	12.00	11.00	11.00	13.00	0.00	0.00	0.00	1.00
	clustering	No sample	95.0	19.0	31.6	23.7	75.6	58.9	39.32	39.88	39.61	43.09	23.18	23.96	24.58	27.34	17.46	17.15	17.00	20.16	0.44	0.40	0.42	0.42	0.00	0.00	0.00	0.00	15.00	12.00	12.00	14.00	0.00	0.00	0.00	0.00
		RUS	94.7	18.4	32.7	23.3	73.1	54.6	39.79	39.61	39.99	45.08	22.92	24.72	25.32	27.75	16.20	17.10	17.71	21.23	0.48	0.45	0.42	0.42	0.01	0.01	0.01	0.02	12.00	11.00	11.00	12.00	1.00	1.00	1.00	2.00
		ROS	94.7	18.3	33.1	23.3	74.5	55.4	38.60	38.24	40.66	45.50	22.23	23.78	25.04	27.40	16.31	16.89	18.00	20.81	0.48	0.41	0.44	0.41	0.00	0.00	0.00	0.01	13.00	11.00	14.00	11.00	0.00	0.00	0.00	1.00
Tree	No cluster	No resampling	95.0	19.0	31.8	23.6	78.7	63.4	40.81	38.28	39.62	44.46	23.21	22.99	24.30	26.22	16.88	16.36	16.49	19.97	0.51	0.44	0.42	0.42	0.00	0.00	0.00	0.02	13.00	12.00	12.00	11.00	0.00	0.00	0.00	1.00
		RUS	95.2	19.3	30.5	23.5	67.4	56.9	39.55	38.71	40.13	42.39	23.44	23.32	24.41	27.06	16.47	17.19	17.17	20.04	0.48	0.40	0.38	0.43	0.01	0.01	0.00	0.02	13.00	12.00	13.00	13.00	1.00	1.00	0.00	2.00
		ROS	95.3	18.6	27.6	22.1	79.2	**64.6**	41.14	39.86	40.37	45.29	23.72	23.78	25.12	26.82	17.89	16.53	16.68	20.14	0.53	0.46	0.44	0.42	0.01	0.01	0.00	0.00	16.00	13.00	11.00	14.00	1.00	1.00	0.00	0.00
		Class weights	95.4	**20.6**	30.4	**24.4**	77.1	62.5	39.79	39.46	39.91	44.58	23.14	23.14	24.09	26.56	16.24	16.51	17.68	20.04	0.46	0.41	0.40	0.41	0.01	0.01	0.00	0.01	12.00	11.00	12.00	12.00	1.00	1.00	0.00	1.00
	clustering	No resampling	95.1	18.9	30.5	23.2	79.8	62.3	41.40	38.81	39.88	43.16	22.98	23.02	24.56	26.75	16.88	16.25	16.89	19.90	0.49	0.42	0.42	0.43	0.01	0.00	0.00	0.01	12.00	13.00	11.00	12.00	1.00	0.00	0.00	1.00
		RUS	95.0	19.4	32.5	24.2	73.8	57.6	39.47	39.53	40.20	44.62	23.12	23.79	23.89	27.49	16.44	17.13	18.00	20.39	0.49	0.40	0.38	0.42	0.00	0.00	0.00	0.00	13.00	10.00	12.00	12.00	0.00	0.00	0.00	0.00
		ROS	95.1	18.3	28.7	22.2	80.1	63.6	40.94	39.70	40.82	44.21	23.36	23.48	24.45	26.60	16.92	16.08	16.80	20.38	0.51	0.45	0.43	0.40	0.01	0.00	0.01	0.01	13.00	13.00	11.00	12.00	2.00	0.00	1.00	1.00
		Class weights	95.4	20.6	30.4	24.4	77.1	62.5	39.53	38.50	40.95	45.12	23.54	23.54	23.94	27.58	16.29	17.34	18.12	20.37	0.48	0.38	0.38	0.41	0.01	0.00	0.00	0.01	12.00	10.00	10.00	12.00	1.00	0.00	0.00	1.00
ZIP	No cluster	No resampling	94.4	14.6	26.8	18.9	74.0	58.0	40.37	40.14	40.15	44.42	25.35	25.07	25.99	26.66	18.53	16.45	17.08	20.81	0.51	0.45	0.41	0.40	0.02	0.00	0.00	0.01	12.00	15.00	12.00	14.00	3.00	0.00	0.00	1.00
		RUS	94.2	13.9	26.1	18.1	61.1	50.6	44.57	45.68	40.89	44.23	25.72	25.43	26.86	27.54	18.93	19.26	16.93	19.91	0.59	0.53	0.51	0.48	0.01	0.02	0.01	0.00	16.00	17.00	15.00	15.00	2.00	3.00	2.00	0.00
		ROS	94.2	13.9	26.7	18.2	61.2	50.6	44.51	45.42	40.70	44.62	25.77	25.48	27.00	27.80	18.88	19.08	16.98	19.76	0.59	0.53	0.51	0.48	0.01	0.02	0.01	0.00	16.00	17.00	15.00	15.00	2.00	3.00	2.00	0.00
	clustering	No resampling	93.1	13.1	31.9	18.5	77.6	61.8	39.35	41.08	40.12	44.97	24.17	24.66	26.42	27.26	18.06	18.40	18.91	20.92	0.47	0.45	0.42	0.37	0.02	0.00	0.01	0.01	13.00	15.00	12.00	12.00	3.00	0.00	1.00	1.00
		RUS	93.0	12.7	30.8	S	74.2	57.1	43.46	41.76	42.50	45.17	24.67	26.08	26.56	28.36	19.36	19.85	17.47	21.08	0.55	0.48	0.49	0.46	0.00	0.01	0.00	0.01	16.00	13.00	15.00	12.00	0.00	1.00	0.00	1.00
		ROS	93.0	12.8	30.9	18.0	74.3	57.0	43.57	41.31	42.71	45.08	24.77	26.13	26.41	28.52	19.32	20.02	17.29	20.98	0.57	0.49	0.48	0.45	0.00	0.01	0.00	0.01	17.00	13.00	15.00	12.00	0.00	1.00	0.00	1.00

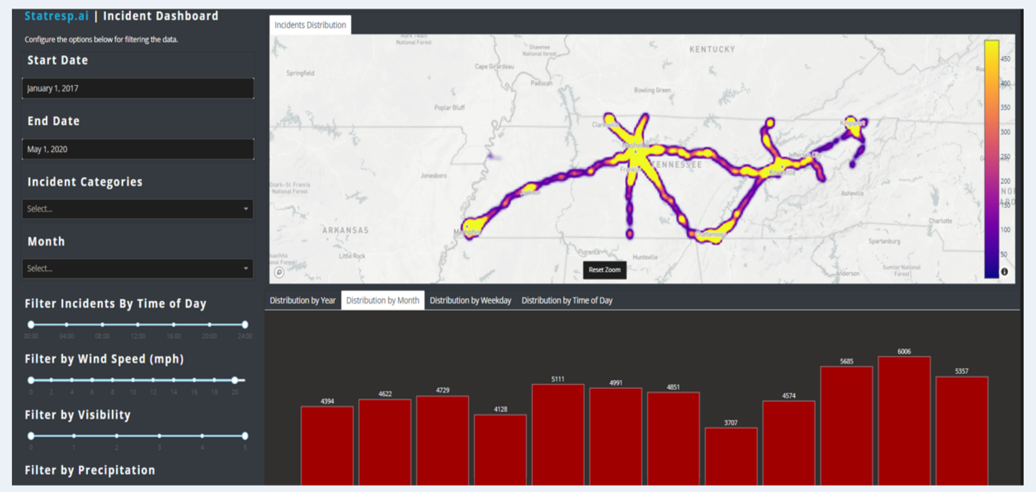
Green cells show better performance in each column. Neural Network and Random forests are best performing models

Balancing Term



α controls the penalty on increased load on responders. Our empirical results show that $0.5 \le \alpha \le 1$ results in the optimal allocation.

Dashboard



Conclusions

- Understanding incident likelihood and resource demand across fine-grained road structure is hard. We have developed a set of techniques and models that can estimate the likelihood well for 20 % of the segments that see 80% of the incidents.
- We are working on a different set of techniques to handle extreme sparsity for the other segments. Future work includes development of detection and design of allocation and dispatch algorithms.

https://github.com/StatResp/KDD_IncidentPrediction

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