Predicting Emergency Medical Services (EMS) Call Volumes







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- Emergency Medical Services [EMS]: Public health service of paramount importance to stakeholders: our families; taxpayers; medical care personnel; local and state governments.
- **Challenge:** Allocation of scarce resources.
- **Data:** Rapidly expanding central national EMS event online database maintained by NEMSIS (<u>https://nemsis.org/</u>) with call time and category *anonymised* by state and county.
- **Aim:** Apply time-series methods to predict call volume for local call centers (agencies), so adequate resources can be deployed in advance.







Data Engineering



- Data from 2018-2023 graciously approved for our use by NEMSIS.
- Anonymized state and county event tables provided in SAS format.
- We (& GPT) **transformed data to SQL database** via sqlite3 together with bash and python wrappers to create .db files totalling ~1 TB
- External tables are **queried with sqlite3** and joined on location code and event type.

Preprocessing

- We modeled call volumes on the state or county level.
- Seasonality motivated us to try a SARIMA model.
- Scaled each year of data to create a stationary dataset and to account for onboarding of new EMS agencies.



SARIMA Model Selection



- Autocorrelation demonstrates weekly seasonality.
- Other SARIMA parameters were selected using the Akaike information criterion to account for overfitting.

State Space Models:

Exponential Smoothing

- Simple, interpretable, computationally efficient.

Facebook Prophet

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- Complex, many parameters, models multiple scales of seasonality.

Facebook Prophet with lockdowns set as holidays



Plot: exponential smoothing, Prophet, and naive model predictions

Combining the state-space models with SARIMA

Strategy:

- Extract trend with moving average
- Compute detrended data
- Predict each component separately:
 - Apply a state-space model to trend component
 - Apply SARIMA to remainder component
- Hyperparameters:
 - Window size for the moving average
 - Type of decomposition into trend and detrended data



Results on test counties:

Model with the **best average normalized mean square error** (NMSE) in testing was **Exponential-Smoothing +** SARIMA

Model with the next best average NMSE was **SARIMA**

(NMSE=MSE of model/MSE of naive model)



y=normalized mean square error (nmse) of exp-smoothing+arima x=logarithm of dataset size

PFR55 (Dataset Size: 3,324,626)			
Model	MAE	NMSE	
smoothing_arima_mult_120	333.955	0.7836	
arima	363.000	0.9510	
constant_predict	415.898	0.5651	
naive_predict	488.711	1.0000	
expsmoothing_predict	643.448	2.1422	

Long Short Term Memory Networks (LSTMs)

	Date	2301071	2301061	2301033	everythingElse	Year	
0	2018-01-01	1	5	8	13	2018	
1	2018-01-02	4	3	0	17	2018	
2	2018-01-03	2	5	4	17	2018	
3	2018-01-04	3	5	6	20	2018	
4	2018-01-05	1	3	4	20	2018	Input, eq. 6 day window
5	2018-01-06	1	2	5	13	2018	
6	2018-01-07	0	3	3	14	2018	
7	2018-01-08	2	6	1	21	2018	J
8	2018-01-09	0	7	4	12	2018	← Target, the 7th day
9	2018-01-10	1	12	3	10	2018	



Data Collection, Size of County

Comparison of all models on a difficult county



How we helped:

- More accurate predictions of EMS call volume can help **optimize efficient scheduling of EMS personnel**.
- Data on model performance will help stakeholders decide whether or not it is feasible to implement forecasting in their jurisdiction.
- We recommend that EMS agencies make consistent data collection and reporting a priority to ensure accurate forecasting.

CBS EVENING NEWS

U.S. faces shortage of EMTs, nearly onethird quit in 2021

