### Sober Thruths

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#### Problem Statement<a class="anchor" id="Problem-Statement"></a>

Predict the number of fatalities and alcohol-impaired driving crashes.

Sober truths:

#### Summary<a class="anchor" id="Summary"></a>

Can we predict the number of pedestrian fatalities?

What measures can we recommend to reduce the number of fatalities? Those caused by alcohol impaired drivers?

Which Machine Learning models should we consider?

How do we compare the performance of the models and pick one?

Can we determine how far out are our models accurate?

Which metrics are most relevant?

We collected data from the National Highway Traffic Safety Administration **(**[NHTSA File Downloads | NHTSA](https://www.nhtsa.gov/file-downloads?p=nhtsa/downloads/FARS/)) from 2010 to the most current data of 2020.

We will use a multivariate Time Series model and a Recurrent Neural Network to train a model to make our predictions.

We will determine which evaluation metrics are most relevant in our scenario.

We will also verify the performance of our model and see how close our predictions are and how well we could extend this for …

#### Data Dictionary<a class="anchor" id="Data-Dictionary"></a>

The data from NHTSA is very comprehensive and contains detailed information on fatal accidents from 1975 to 2020. We will use the data from 2010 to the most current 2020.

#### Input Data

#### Output Data files

\* [`accident\_ts\_10years.csv`]( ./data/accident\_ts\_10years.csv): Data from the NHTSA FARS dataset

#### Image files

For presentation purposes

#### Methodology<a class="anchor" id="Methodology"></a>

\*\*Forecasting using VAR TimeSeries and RNN models:\*\*

\*\*Fatals accident data - EDA and Visualizations\*\*

EDA: Looked at the large number of pre-crash conditions, road surface conditions, driver distractions including by a mobile device or texting, vision obscured by rain/snow, construction zone, maneuvering to avoid another vehicle or pedestrians or bicyclists, contributing factors like tires, brakes or headlights, bad weather or poor lighting conditions, among others. Also looked at state, city and lat/long data. This is a very rich set of data and there is literally no limit to the amount of Eda once can do.

For the time series model, I was able to use the NHTSA accident dataset directly since this has all the drunk driver, pedestrians, vehicle and persons information aggregated for a crash. Creating a datetime index, resampling by day, week and month generated the dataframes necessary for modeling by day, week and month respectively.

\*\*3 Hour window:\*\*

Looking at visualizations by year, month, week, day of week or hour of day did not give too many insights other than the trend of fatalities, drinking drivers and pedestrians killed has been mostly increasing over the years.

A key discovery from the EDA and external research was that weekend nights have more accidents and a larger percentage are caused by drinking drivers. This led to creating shorter periods of 2, 3 and 4 hours to determine patterns. \*\*This was huge\*\*

This led me to dive a lot deeper into the dataset using this 3 hour window to determine the causes and potential ways to reduce the fatalities during the worst times.

Details in subsequent sections.

\*\*Model Selection:\*\*

The dataset contains sequential temporal data and is hence a good candidate for time series based models.

The two most popular models for time series forecasting are AutoRegressive and RNN.

1. Among AutoRregressive options like ARIMA, SARIMAX etc, I chose the Vector AutoRegressive (VAR) model since it is a bi-directional multivariate forecasting algorithm where two or more time series influence each other. In our case, the number of fatalities, alcohol-impaired drivers, pedestrians killed, vehicles and persons involved influence each other. Each of these variables is modeled as a linear combination of past values of itself (lags) and the past values of these other variables.

Used correlation to confirm that these influence each other and hence can use the VAR model to forecast all five variables.

Did the diff and used the ADF (Augmented Dickey Fuller) statistical Test to confirm stationarity of the time series variables.

The coefficient of correlation between two values in a time series, called the autocorrelation function (ACF) was used to identify seasonality in our time series data.

The ACF plot, a bar chart of the coefficients of correlation between a time series and lags of itself, was used to pick the points that are statistically significant (outside the blue shaded Confidence Interval region).

Partial autocorrelation (PACF), a statistical measure that captures the correlation between two variables after controlling for the effects of other variables, was used to confirm the statistically significant lags.

We then decomposed the three parts of a time series – the trend, seasonality and residuals for all 5 variables.

Then came the traditional instantiate, fit, predict and evaluate.

1. Recurrent Neural Networks are deep learning models used to solve problems with sequential input data. I used the same five variables in the RNN model, as all the inputs are related to one another, to enable easier comparison between the two models.

Similar to linear regression models, and unlike the time series, these variables are like the X variables used for predictions and the target variable is just the fatals.

I used a small train test split 2% and the Keras TimeseriesGenerator to feed 16 sequences (batchsize) of length of 3 (and 5) through our model. Our validation data set is small (only 81 rows) so chose a small batch size of 16.

LSTM (long short-term memory) and GRU (Gated Recurrent Units) can alleviate the vanishing gradient problem which is a known shortcoming of RNNS especially with long time series extending over hundreds of periods. Along with Regularization using Dropout layers and EarlyStopping for optimization, I was able to get to a reasonably performing predictive model.

\*\*Model Evaluation:\*\*

Used RMSE and MAPE to see how far off are predictions are in absolute numbers (in the same units as our target) and in percent terms.

## Findings and Observations<a class="anchor"id="Findings-and-Observations"></a>

\*\*EDA:\*\*

Started with 356445 records for 11 years, after cleanup 353764.

A picture containing chart

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\*\*Interpretation:\*\*

The largest number of alcohol-impaired driver (AID) involved fatal crashes is Sunday midnight to 3am i.e. late Saturday night, followed by Saturday midnight to 3am, i.e. late Friday night.

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**#### \*\*Interpretation\*\* :**

In 2020, 55% of fatalities were caused by drinking drivers during the worst 3 hour window of Sunday midnight to 3am.

Overall across all 11 years, it was 57%.

In 2020, there were 38491 fatalities. Average of 105 per day, or 4.4 per hour

During the worst 3 hour window of Saturday 21:00 to 24:00, there were a total of 1273 fatalities in 2020, average of 24.5 per week per this 3 hour window, i.e. 8.1 per hour. During Labor Day, it went up to 11 per hour.

This is 1.84 times the hourly average of 4.4.

In 2020, there were 9415 drinking driver fatalities. Average of 25.8 per day, or 1.1 per hour

During the worst 3 hour window of Sunday 0:00 to 3:00, there were a total of 610 drinking driver fatalities in 2020, average of 11.7 per week per this 3 hour window, i.e. 3.9 per hour. During Labor Day, it went up to 5.6 per hour.

This is 3.5 times the hourly averge of 1.1

Percent:

In 2020, 24.5% of fatalities (9415 out of 38491) involved drinking drivers. During weekend nights, this percent went up to 55%. During Labor Day, it went up to 89.5%

Holidays:

Labor Day:

Sunday 0:00 to 3:00 **\*\*19 17\*\*** 1 Labor Day 89.47

Saturday 0:00 to 3:00 20 15 7 Labor Day 75.00

Sunday 21:00 to 24:00 **\*\*33\*\*** 9 9 Labor Day 27.27

Saturday 18:00 to 21:00 32 13 3 Labor Day 40.62

Chart

Description automatically generated

**#### \*\*Interpretation\*\* : 57% of all fatalities are caused by drinking drivers on Saturday and Friday nights.**

Only 7% of fatalities are caused by drinking drivers on Wednesday and Thursday from 9am-noon.

\*\*Holidays:\*\*

Another key finding was that during the major holidays – Labor Day, Memorial Day, New Year’s Day the percent of AID involvement shot up to as much as 90%

Chart, bar chart

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**#### \*\*Interpretation\*\* :**

During Holidays, there are many more fatalities caused by drinking drivers than during the worst 3 hour windows on non-holidays.

During the Labor Day weekend, 90% of the 19 fatalities were caused by drinking drivers on Sun between midnight and 3am, and 75% of the 20 fatalities on Sat between midnight and 3am. Both these percentages are well above the 55% of drinking driver fatalilities on non-holiday weekends.

In 2020, of the total 9415 drinking driver fatalilites, 803 (8.5%) were during the 6 holidays. Fatalities were 2412 (6.3%) during the Holidays

Holidays: 803, 2412; 2020: 9415, 38491

Sunday 0:00 to 3:00 **\*\*19 17\*\*** 1 Labor Day 89.47

Saturday 0:00 to 3:00 20 15 7 Labor Day 75.00

Sunday 21:00 to 24:00 **\*\*33\*\*** 9 9 Labor Day 27.27

Saturday 18:00 to 21:00 32 13 3 Labor Day 40.62

\*\*VAR modeling Findings:\*\*

Used a Train Test Split of 5% since forecasting works better for small time periods and our monthly time series for 11 years has only 132 data points. Using maxlags during fitting, the order of the timeseries (number of lags used in the model) is 13. There are no other hyper-parameters to tune, except to ensure that the time series is stationary.

Monthly – need one diff to make stationary. Weekly and daily were already stationary.

Chart

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\*\*Interpretation\*\* :

The forecast does a pretty good job in following the actual curve except where the data spikes suddenly.

\*\*Model Evaluation:\*\*

The test RMSE is substantially better than the baseline RMSE, for all 3 variables. For fatals, the test RMSE of 503 is 34% better than the baseline of 761.9.

The Mean Absolute Percent Error (MAPE) which shows the percent error indicates that our model’s forecast for fatals is off by 14% on an average month or 503.

The forecast for the peds is the most accurate, its off by 8% or 67 peds per month, in an average month.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Baseline RMSE** | | | **Test RMSE** | | | **Baseline MAPE** | | | **Test MAPE** | | |
| fatals | drunk\_dr | peds | fatals | drunk\_dr | peds | fatals | drunk\_dr | peds | fatals | drunk\_dr | peds |
| 761.98 | 190.04 | 190.04 | 503.66 | 139.41 | 67.09 | 0.20 | 0.14 | 0.23 | 0.14 | 0.14 | 0.08 |

\*\*RNN:\*\*

The daily time periods spanning 11 years has a total of 4018 observations, of which the validation data of 2% is 81 observations.

Tried various models with varying sequence of length size and LSTM and GRU layer with regularization, different number of hidden layers and nodes and Dropout.

The params for the best model are in a later section.

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\*\*Interpretation:\*\*

The predictions are quite good, more so in the first few days. Over the total 81 days of predictions, the predictions don't quite match the peaks. In fact, towards the end they overshoot the data considerably.

Chart

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#### \*\*Interpretation:\*\*

The graphs are almost perfect! The testing RMSE is marginally higher than the Training RMSE, showing the model is not overfit and should do a good job on predicting new unseen data.

\*\*Model Evaluation:\*\*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Baseline RMSE** | **Training RMSE** | **Test RMSE** | **Baseline MAPE** | **Training MAPE** | **Test MAPE** |
| 23.25 | 14.69 | 15.32 | 0.15 | 0.12 | 0.10 |

The RMSE and MAPE confirm the graphs. The Training RMSE is substantially better than baseline and the Test RMSE is only marginally higher than the Training RMSE.

This indicates that our model’s forecast for fatals is off by 10% on an average day or 15.

![Comparision of models]

## Best Models<a class="anchor" id="Best-Models"></a>

![Top Model]

Best Params:

## Conclusions<a class="anchor" id="Conclusions"></a>

RNN did better, though VAR gets to forecast on more than one variable.

## Next Steps<a class="anchor" id="Next-Steps"></a>

- Need to tune the models to improve performance (time consuming and CPU intensive)

- Room for improvement:

- Try Linear Regression with exogenous variables – weather, distracted, construction zone

- VAR: investigate how to improve weekly and daily forecasts

- RNN: Can try weekly and monthly resampling to compare with VAR. Could try further hyper-parameter tuning

- Clean up warnings:

- UserWarning:

## Bibliography <a class="anchor" id="Bibliography"></a>