# Road Accident Prediction and Severity Analysis

TEAM MEMBERS: PRAMIL PAUDEL, SUMIT BHATTARAI

#### **Background and Facts:**

- There were 33,654 fatal motor vehicle crashes in the USA in 2018
- In 2018, 36,560 deaths occurred in the M/V crashes in the USA
- 11.2 deaths/100K people and 1.13 deaths/100k Miles of travel

Source: National Highway Traffic Safety Administration

#### Data Source:

- This is a countrywide car accident dataset, which covers 49 states of the USA.
- The accident data are collected from February 2016 to June 2020.
- There were 3513617 ( 3 Million ) unique data.
- USA FIPS (Federal Information Processing Standards ) data was used for county wise plotting.
- Link to data: <a href="https://www.kaggle.com/sobhanmoosavi/us-accidents">https://www.kaggle.com/sobhanmoosavi/us-accidents</a>

Note: Data is available for research/academic purpose.

#### **Project's Purpose:**

- Data Visualization
- Severity Analysis (EDA)
- Classification
- Time Series Forecasting

**Project's Purpose:** 

## VISUALIZATION

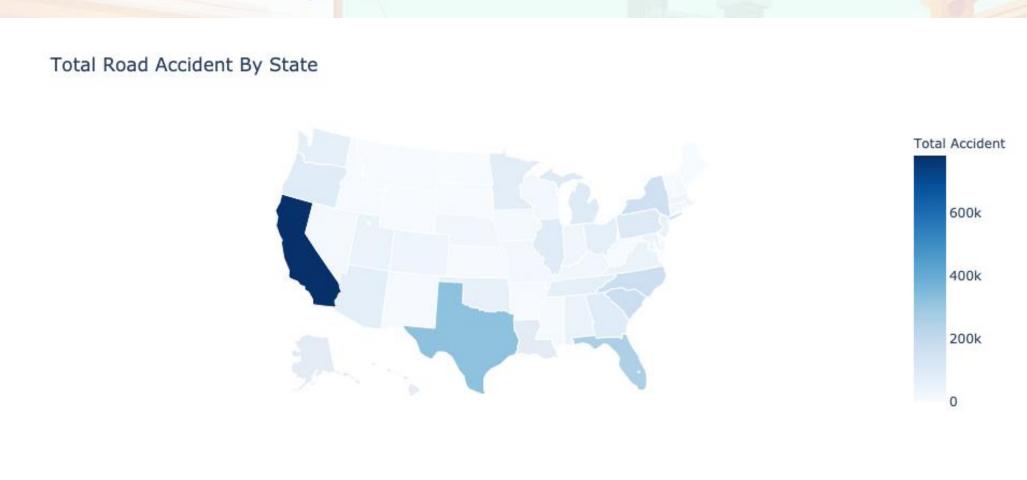
#### **Data Visualization:**

- Data are visualized using different properties like State, City, Day, Hours by aggregating their count.
- Data are visualized using day, month, and year.
- Accident count are plotted against City and Time too

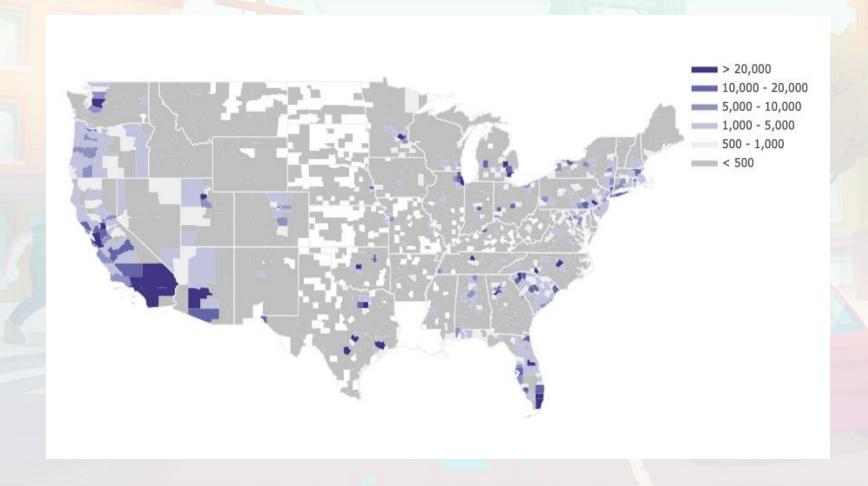
Data Visualization: Before Plotting in USA Map

- There were many cases having State and Zipcodes values N/A dropped.
- For better visualization source data was merged with USA geographical information to get FIPS (Federal Information Processing Standards ) code
- Some attributed like Precipitation, Wind\_Chill(F) containing many NA values were dropped to make data light weighted for easy processing
- These processed were applied only when they were applicable.

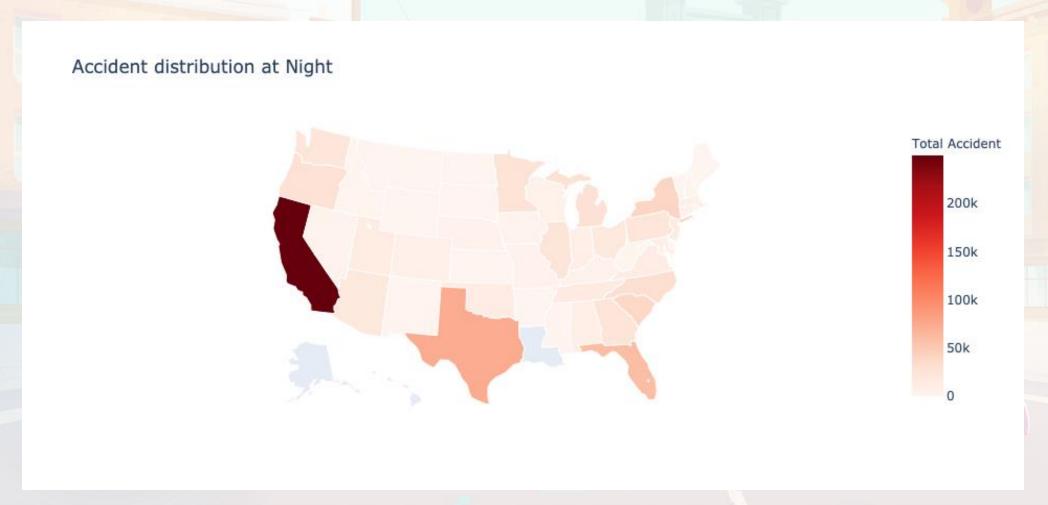
#### **Data Visualization:**



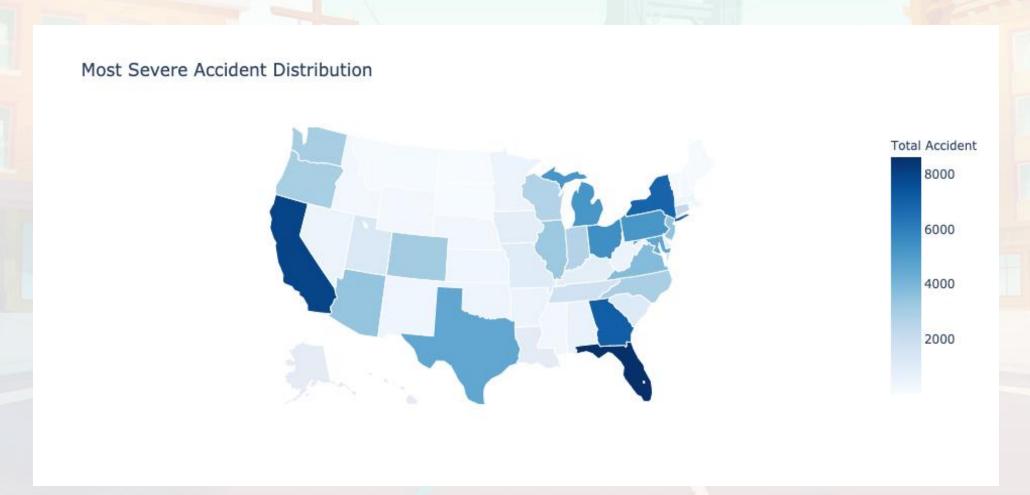
Data Visualization: Total Accidents in county level



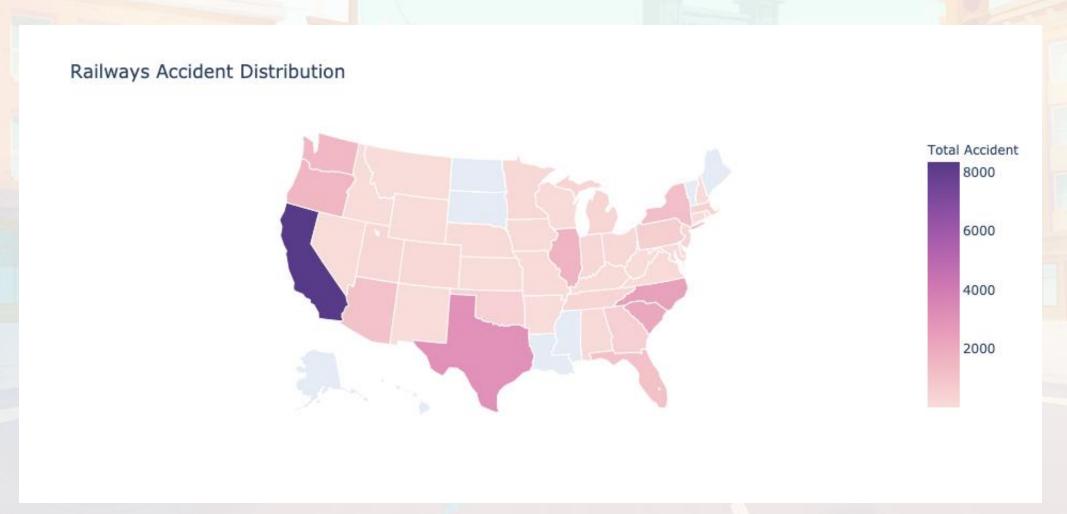
Data Visualization: Total Accidents in county level



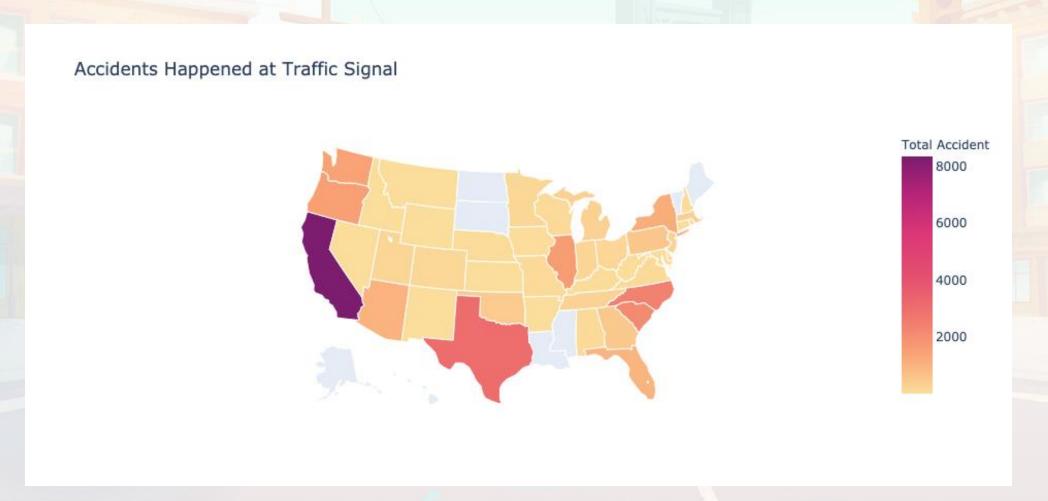
Data Visualization: Most severe accidents distribution



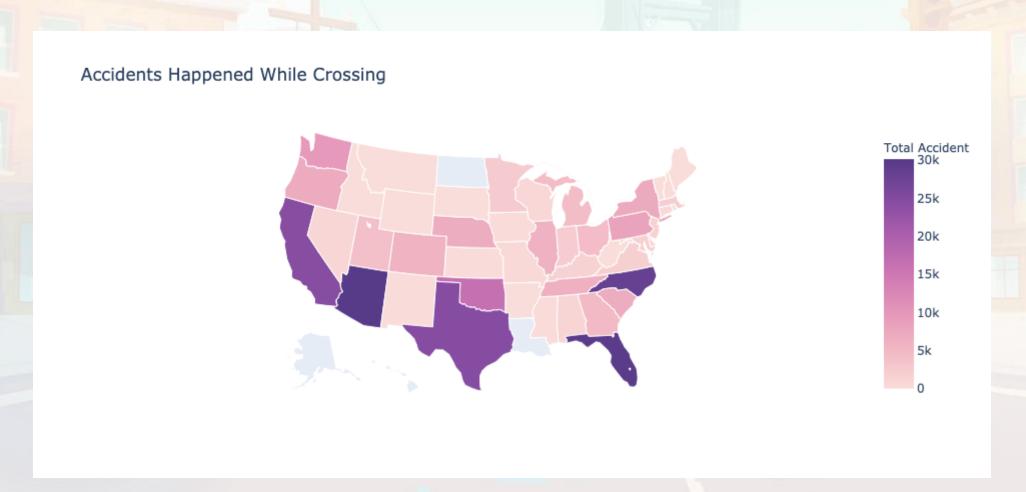
Data Visualization: Distribution of accidents due to railways



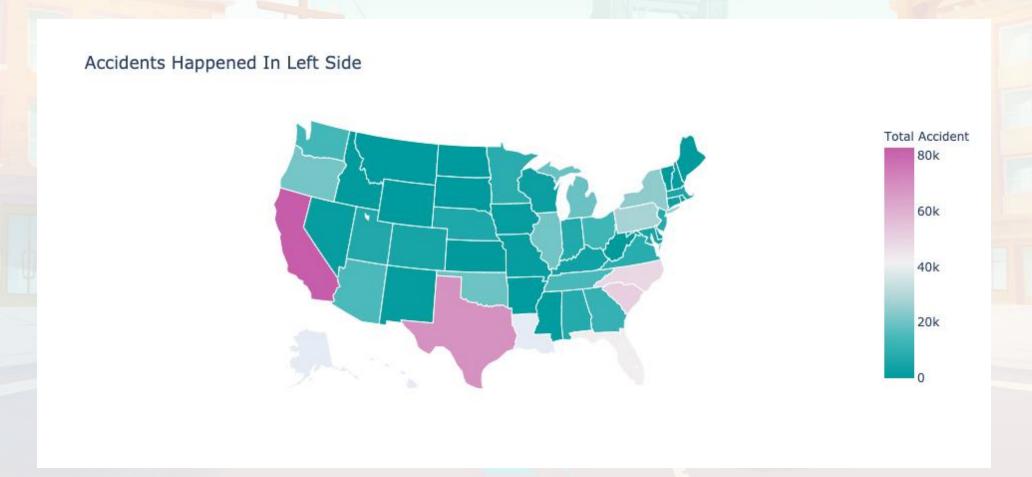
Data Visualization: Distribution of accidents -> Traffic Signal



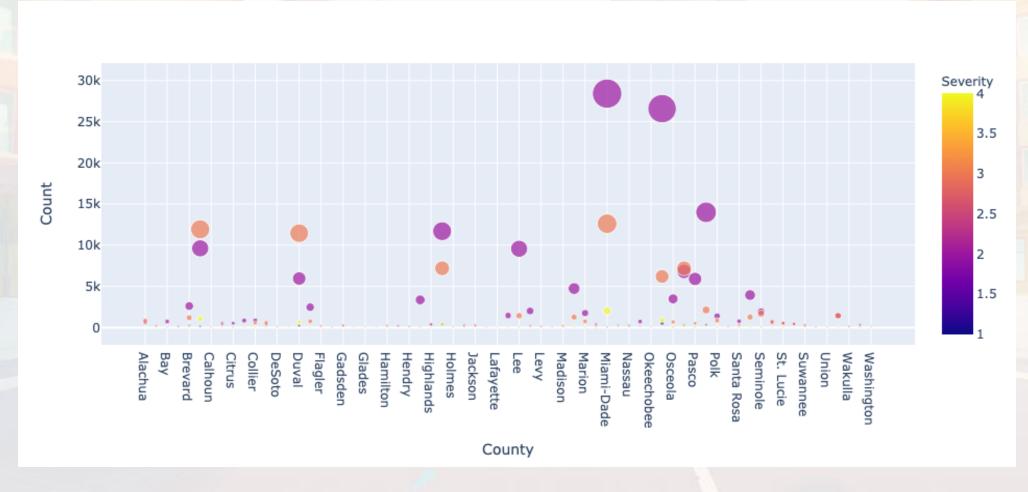
Data Visualization: Distribution of accidents -> While Crossing



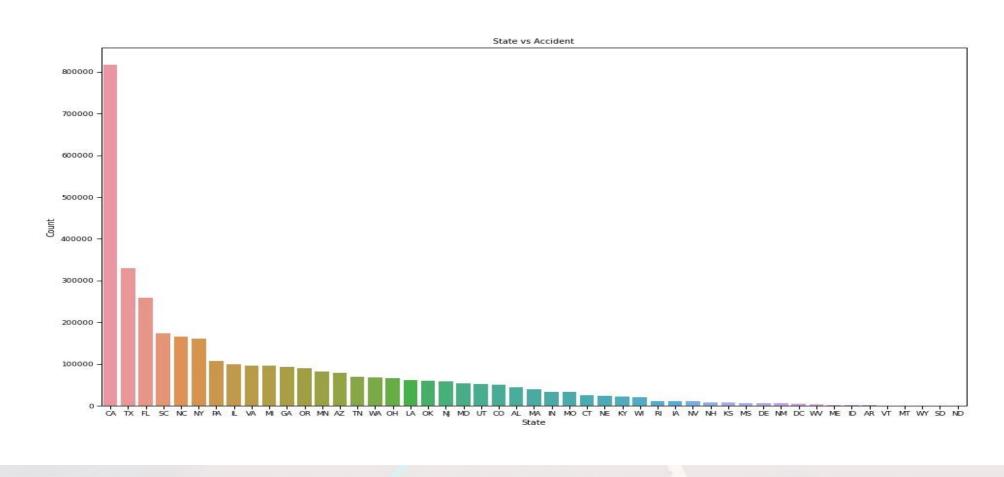
Data Visualization: Distribution of accidents -> Left Side



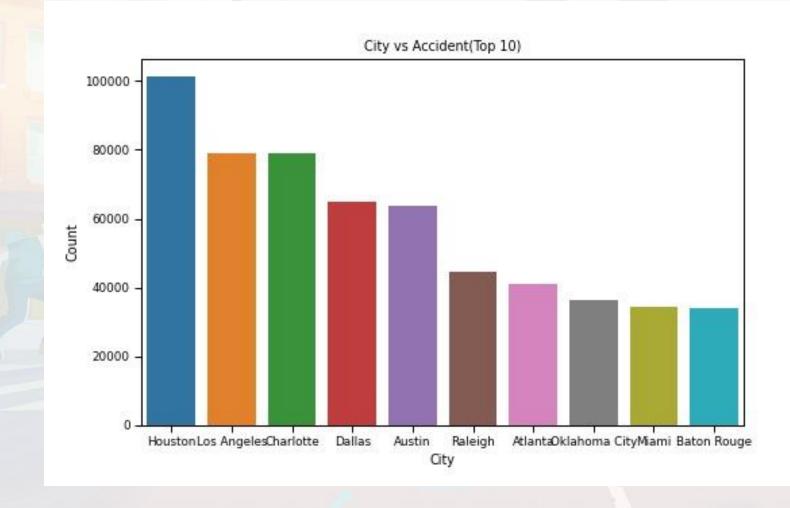
Data Visualization: Distribution of accidents -> Florida Counties



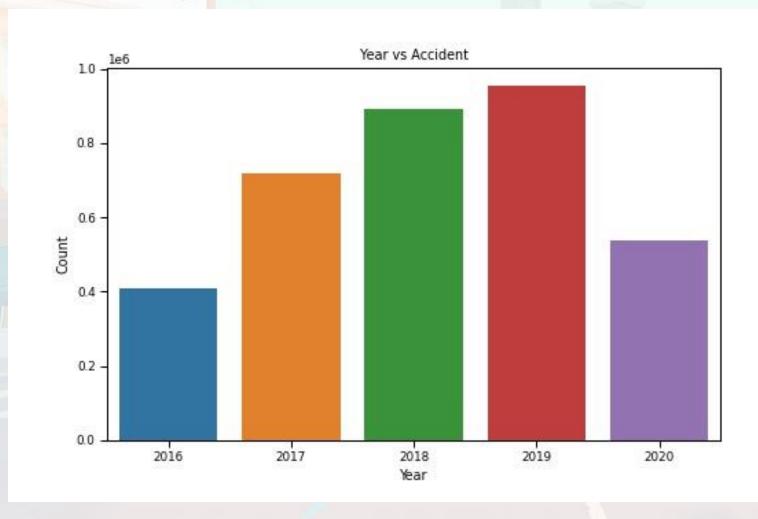
#### State vs Accident



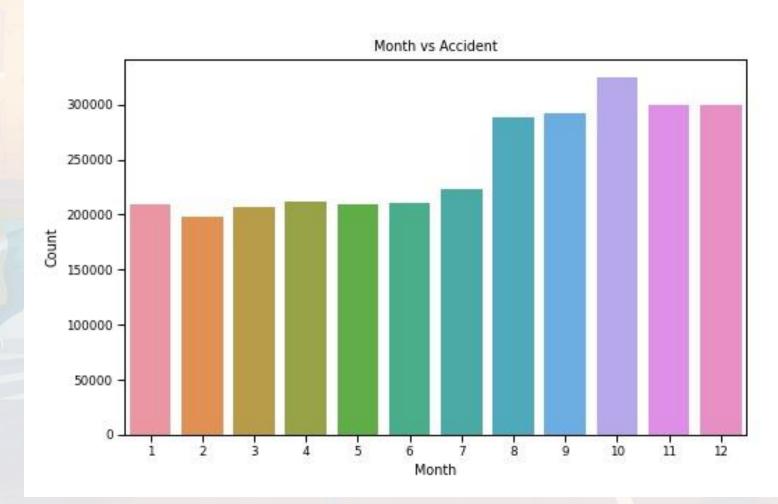
#### City vs Accident(Top 10):



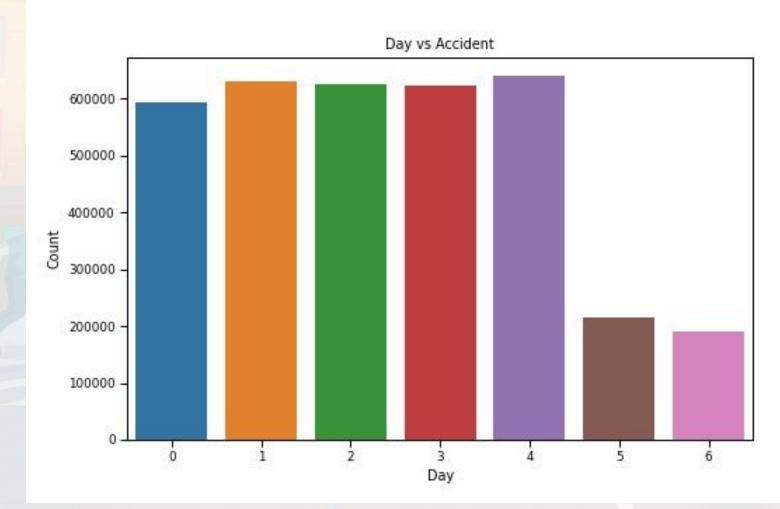
#### Year vs Accident:



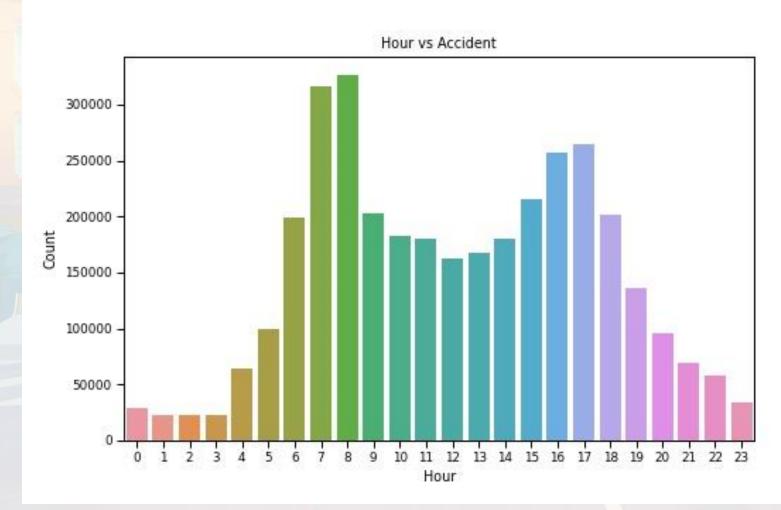
#### **Month vs Accident:**



#### Day vs Accident:



#### **Hour vs Accident:**



#### Result -> Visualization:

- Most Populous state and Cities has highest number of accident.
- The accident number is increasing every year.
- For year 2020, data is available until June and it is already greater than half of 2019.
- The accident was highest in October and overall it occurred more in last five month of the year. (Plot excludes 2020 data)
- October is designated as 'National Pedestrian Safety Month'.
- As expected, accident are higher during weekdays.
- Most of the accident occurred during commute hour/rush hours.

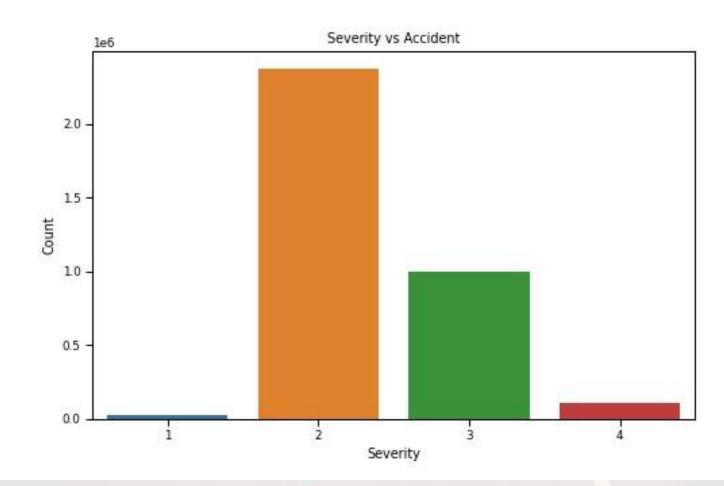
Data Visualization: Distribution of accidents due to railways

# Severity Analysis

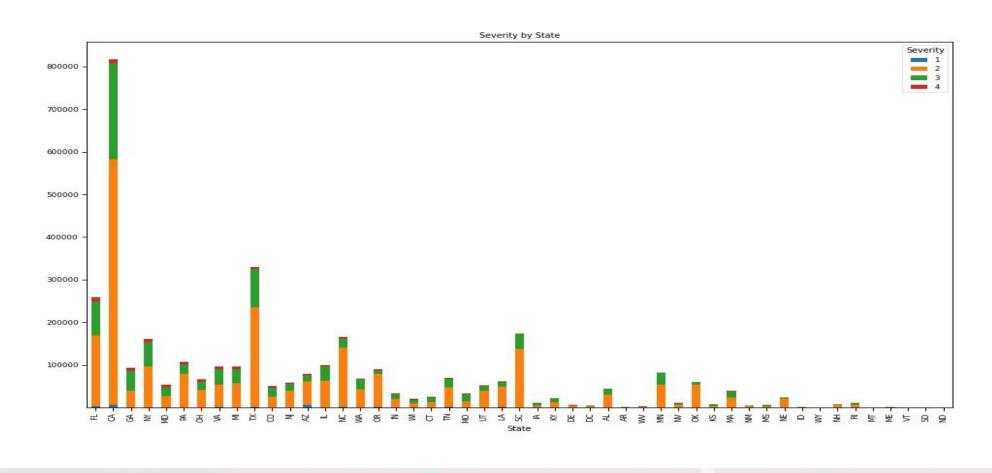
#### **Severity Analysis:**

- The data is aggregated with respect to severity for different properties.
- Stacked bar plot is used to analyze the data.
- The data is later converted to percentage/rate of severity and are analyzed with respect to different properties.

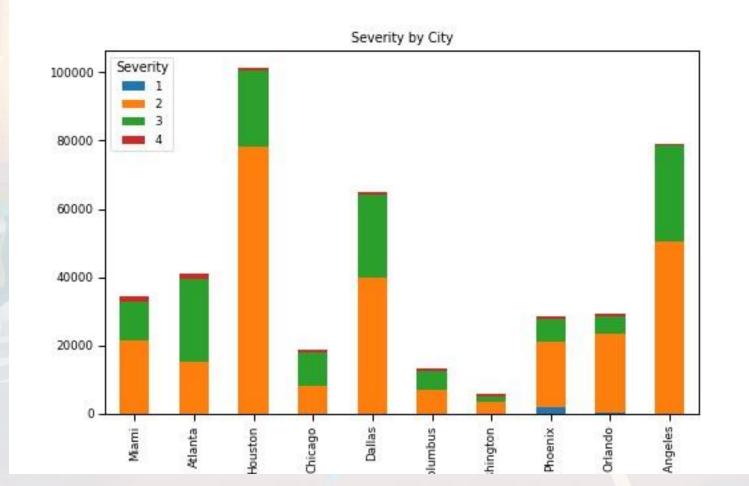
#### **Severity Analysis:**



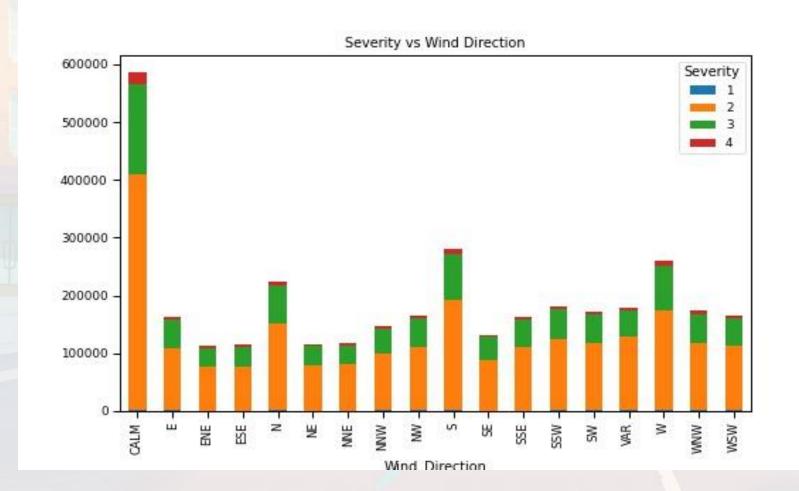
#### Severity By State:



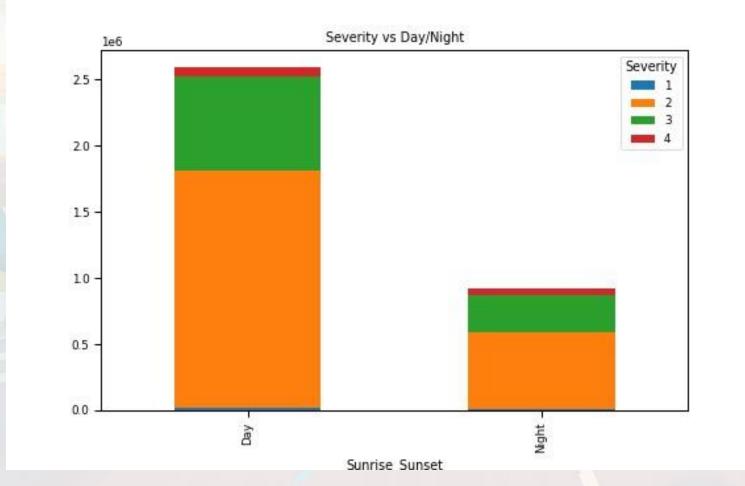
#### **Severity By City:**



#### **Severity Vs Wind Direction:**



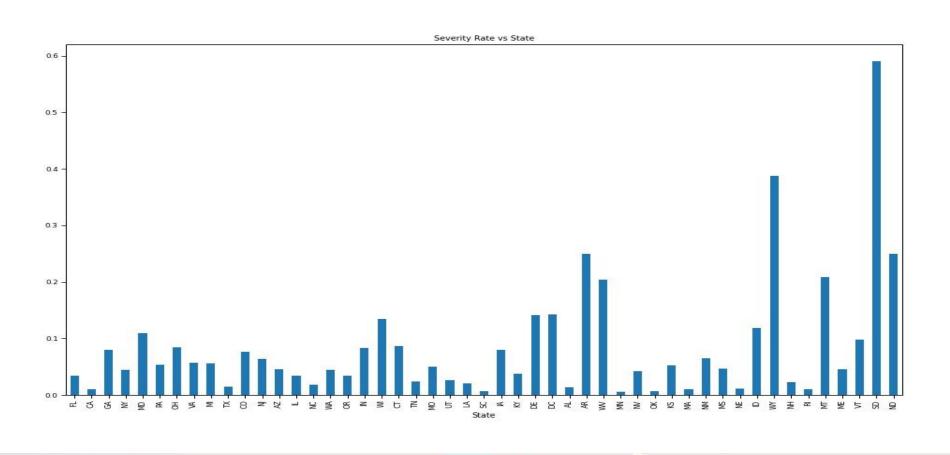
#### Severity vs Day/Night:



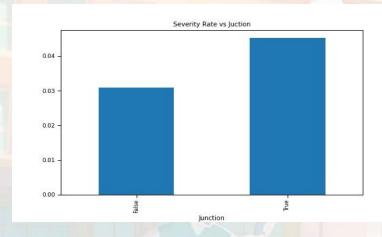
#### Conclusion:

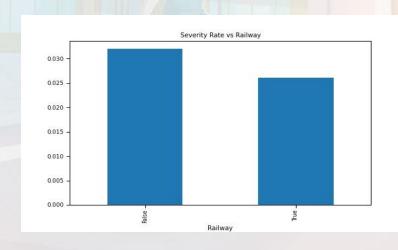
- Most of the accident reported were of level 2.
- Most severe accident occurred in biggest state and cities.
- It was high during day when most of the people commute.
- It was high when the weather direction was normal.
- All the result using count/numbers are expected result. So, let us analyze these along with other properties using the rate/percentage of severity of level 4.

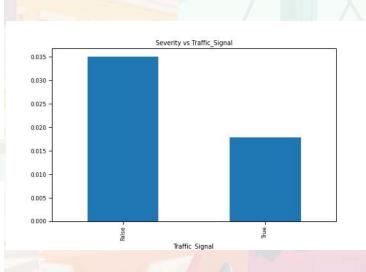
#### **Severity Rate:**

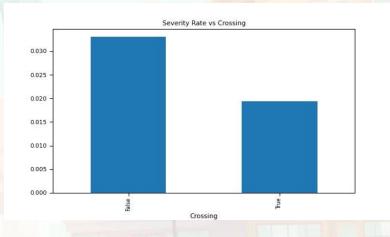


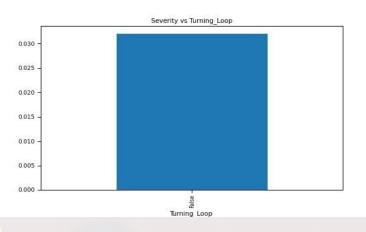
#### **Severity Rate:**





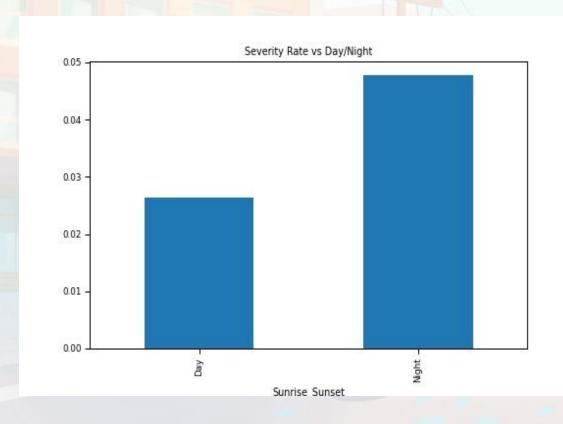


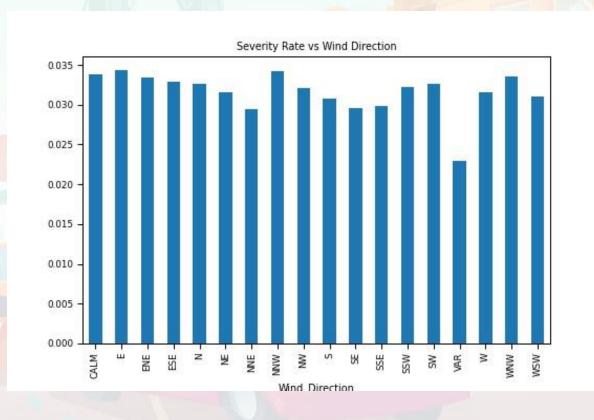




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#### **Severity Rate:**





#### Result -> Severity Analysis:

- State with severe climate condition like South Dakota, North Dakota has highest severity rate.
- Biggest states like California, Florida, etc., has lowest severity rate.
- It seems most of the people are cautious in areas with crossing, traffic signal, turning loops, etc.
- No severe accident were reported in turning loops.
- Severity rate is high for accident reported at Night.
- Almost every wind direction has similar severity rate.



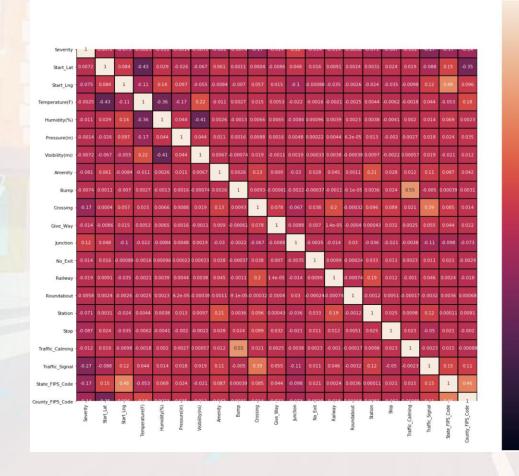
#### Classification:

Following are the assumption made while doing classification

- Sample data of size: 499999, was taken using terminal split over pre-processed data.
- Only 38 columns were selected initially containing non-NA values
- Features sharing only high correlation > 0.05 with targets values are selected.
- Two classifications are used 1. Decision Tree 2. KNN

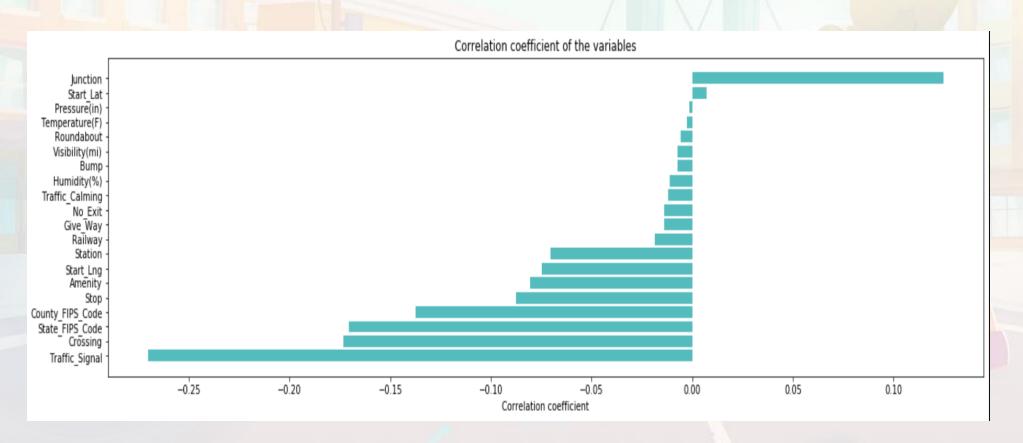
Classification: feature selection

At first correlation heat map was produced for many features



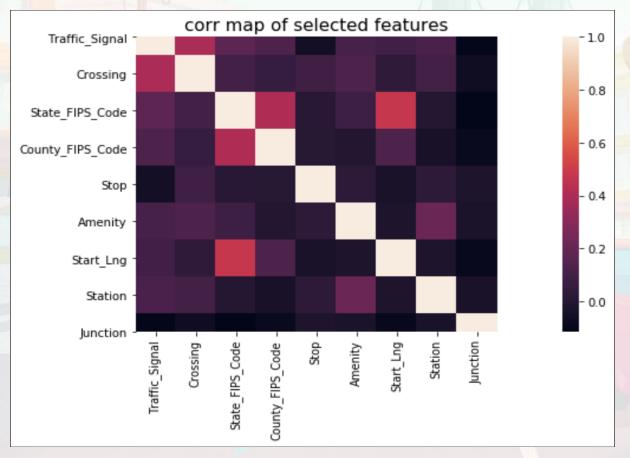
#### Classification: feature selection

- Correlation values are calculated and plotted as below
- Traffic Signal, Crossing, State, County, etc. have highest correlation factor



## Classification: feature selection

Only features containing more than 0.05 correlation factor are selected.



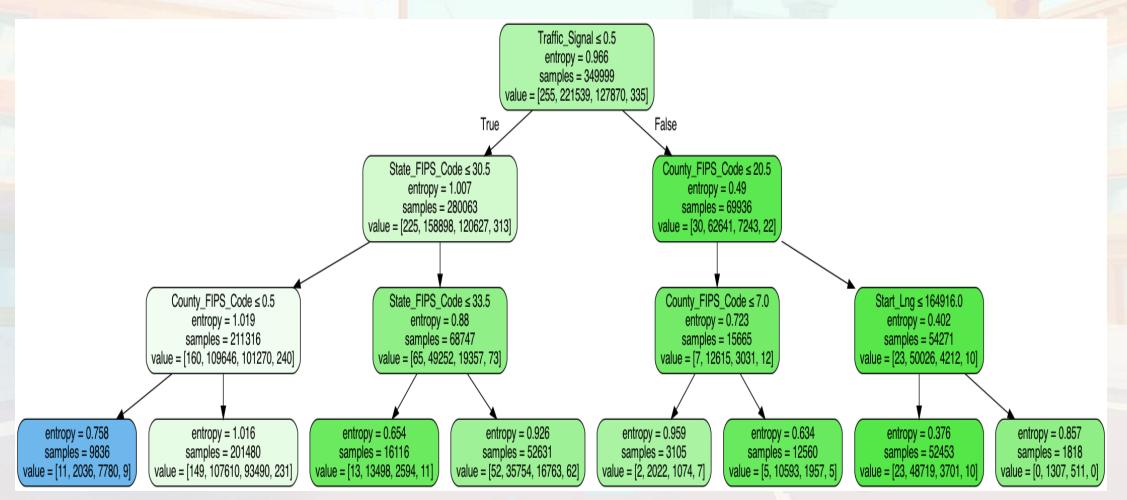
## Classification: Decision Tree Classifier

- There are two Decision Tree Classification are used based on Criteria
  - Entropy where entropies of each features is calculated, and tree is generated.
  - ☐ Gini Tree is generated used Gini Coefficient
- Depth Limitation: Decision tree pruning is applied using predefined tree depth.
  - Classification is tested using different depth.
- 70% Train and 30% Test data is used in classification

## Classification: Decision Tree Classifier -> Entropy

```
Accuracy of Entropy Classifier using 70.0% training and depth 1:::: 0.63601333333333333
Accuracy of Entropy Classifier using 70.0% training and depth 3:::: 0.6519
Accuracy of Entropy Classifier using 70.0% training and depth 5:::: 0.66366
Accuracy of Entropy Classifier using 70.0% training and depth 7:::: 0.70216666666666667
Accuracy of Entropy Classifier using 70.0% training and depth 8:::: 0.72620666666666667
Accuracy of Entropy Classifier using 70.0% training and depth 9:::: 0.7318066666666667
Accuracy of Entropy Classifier using 70.0% training and depth 10:::: 0.74606
Accuracy of Entropy Classifier using 70.0% training and depth 11:::: 0.75547333333333333
Accuracy of Entropy Classifier using 70.0% training and depth 12:::: 0.7715
Accuracy of Entropy Classifier using 70.0% training and depth 15:::: 0.80523333333333334
Accuracy of Entropy Classifier using 70.0% training and depth 17:::: 0.82224
Accuracy of Entropy Classifier using 70.0% training and depth 20:::: 0.84975333333333334
```

## Classification: Decision Tree Classifier -> Entropy



Classification: Decision Tree Classifier -> Entropy -> Observation

### Confusion Matrix

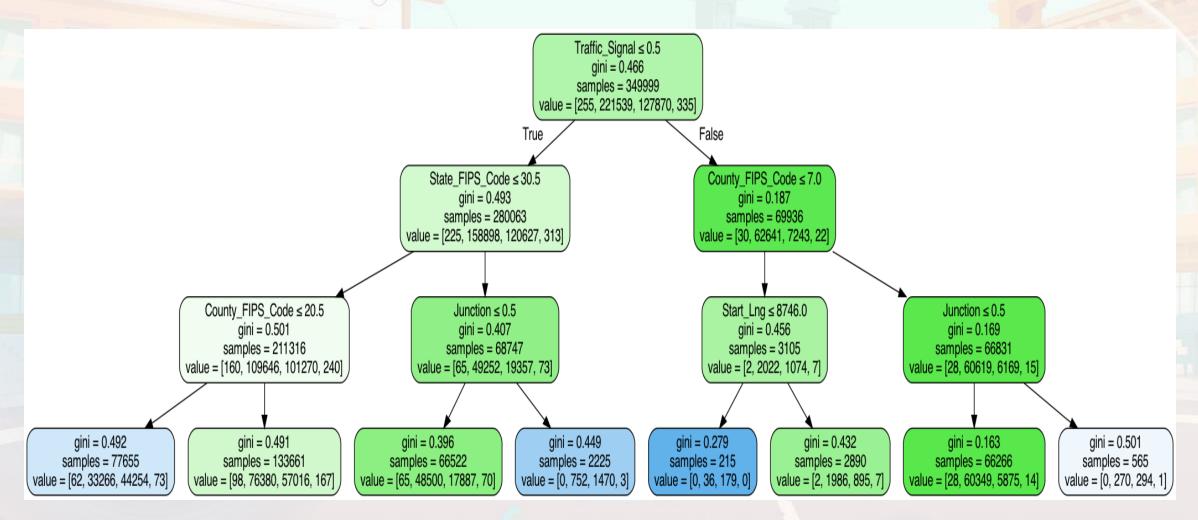
1	80	36	0
33	83861	11496	12
6	10691	43600	35
0	36	112	1

Increased Accuracy with Depth?

#### Classification: Decision Tree Classifier -> Gini

```
Accuracy of Gini Classifier using 70.0 % training and depth 1:::: 0.63601333333333333
Accuracy of Gini Classifier using 70.0 % training and depth 2:::: 0.636013333333333333
Accuracy of Gini Classifier using 70.0 % training and depth 3:::: 0.6663866666666667
Accuracy of Gini Classifier using 70.0 % training and depth 4:::: 0.6819066666666667
Accuracy of Gini Classifier using 70.0 % training and depth 5:::: 0.6943
Accuracy of Gini Classifier using 70.0 % training and depth 8:::: 0.7339066666666667
Accuracy of Gini Classifier using 70.0 % training and depth 11:::: 0.7734
Accuracy of Gini Classifier using 70.0% training and depth 15:::: 0.81742
Accuracy of Gini Classifier using 70.0% training and depth 17:::: 0.833
Accuracy of Gini Classifier using 70.0 % training and depth 19:::: 0.8517666666666667
Accuracy of Gini Classifier using 70.0 % training and depth 20:::: 0.86004
```

#### Classification: Decision Tree Classifier -> Gini



Classification: Decision Tree Classifier -> Gini-> Observation

#### Confusion Matrix

# 1 79 37 0 23 84921 10449 9 3 10217 44083 29 0 37 111 1

Actual

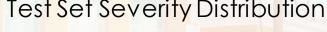
Recall = 
$$TP/(TP+FN)$$
,  
Precision =  $TP/(TP+FP)$ 

Increased Accuracy with Depth?

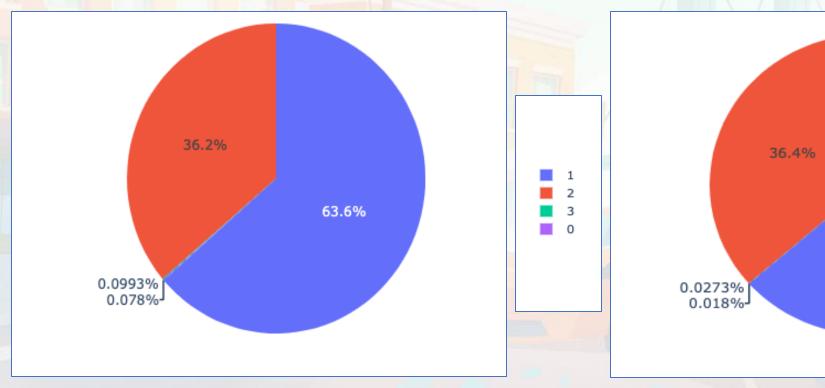
**Predicted** 

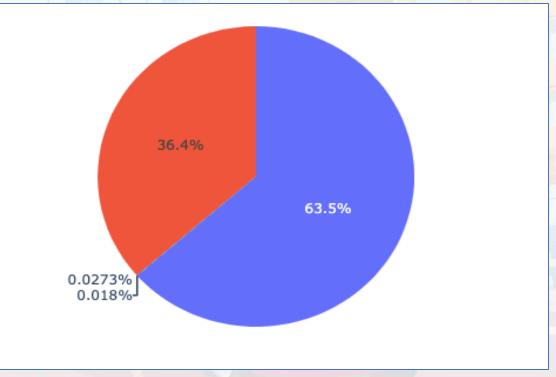
Classification: Decision Tree Classifier -> Gini-> Observation

Test Set Severity Distribution









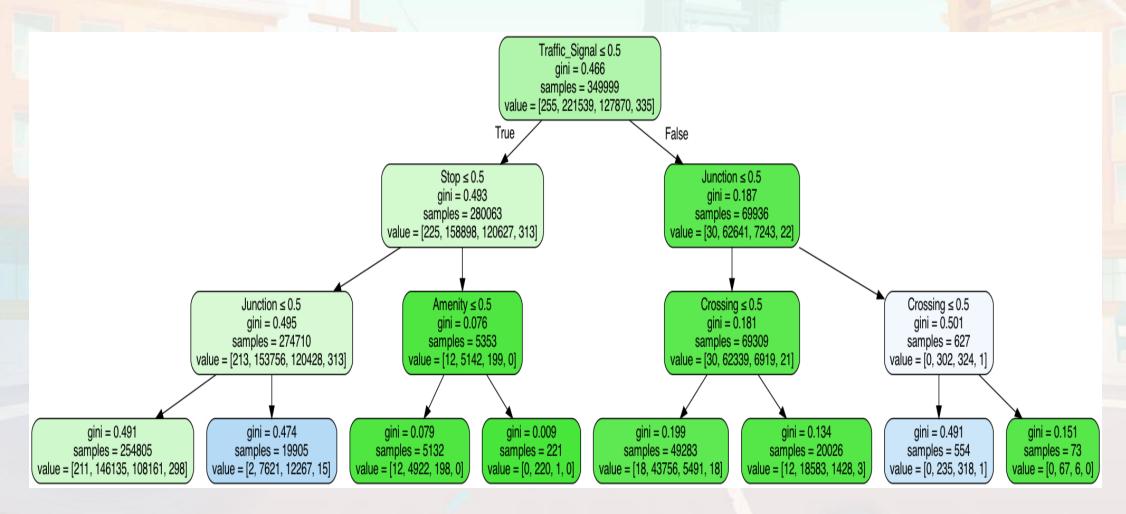
Classification: Decision Tree Classification

- The main reason behind increment of the depth is increasing accuracy is due to presence of continuous variables (having numbers not quantified properly) like State Code, County Code and Lattitude.
- Continuous variable are treated based on variance
- So let's remove these variables from feature list and check...

## Classification: Decision Tree Classification -> Modified Gini

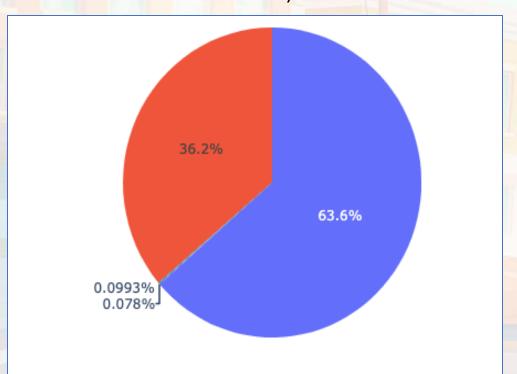
```
Accuracy using Gini Classifier using 70.0 % training and depth 2:::: 0.63593333333333334
Accuracy using Gini Classifier using 70.0% training and depth 3:::: 0.64788
Accuracy using Gini Classifier using 70.0 % training and depth 5:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 6:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 7:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 8:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 9:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 10:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 11:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 12:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 13:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 14:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 15:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 16:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 17:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 18:::: 0.6479
Accuracy using Gini Classifier using 70.0% training and depth 19:::: 0.6479
Accuracy using Gini Classifier using 70.0 % training and depth 20::: 0.6479
```

#### Classification: Decision Tree Classification -> Modified Gini

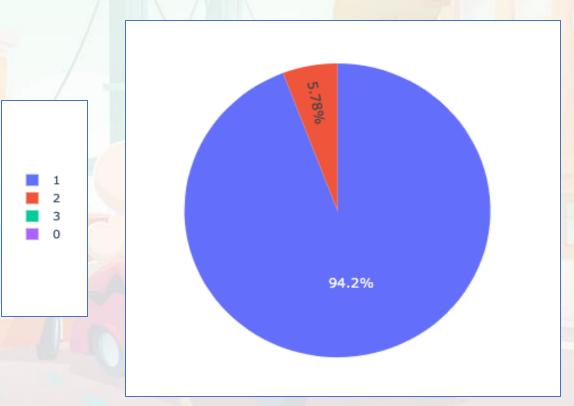


Classification: Decision Tree Classifier -> M. Gini-> Observation

Test Set Severity Distribution



Classified Severity Distribution (modified Gini)



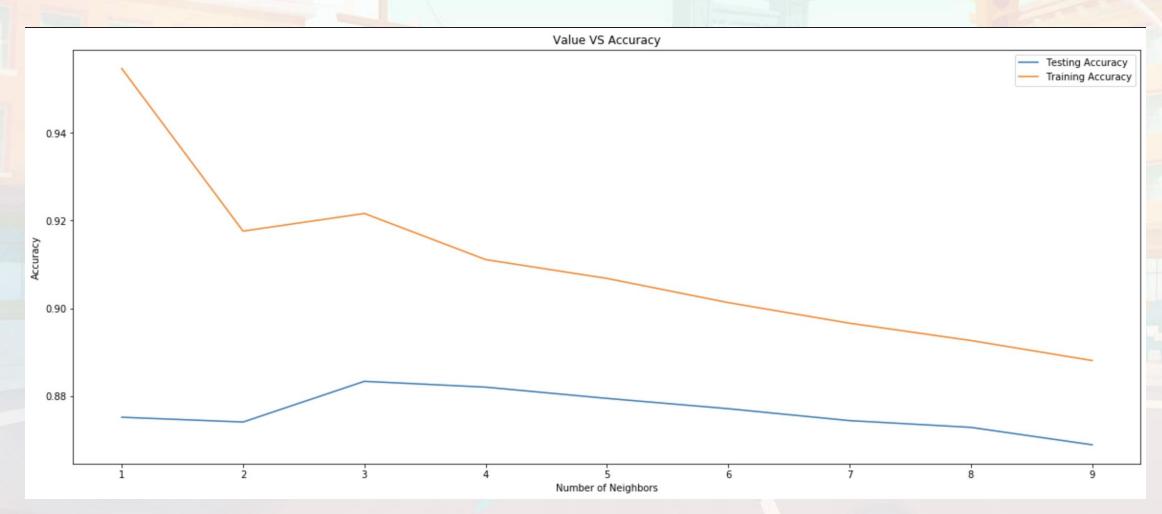
Classification: Decision Tree Classification -> Result

- Geographical Information are important for classification ( to be included in features)
- Around 86% of accuracy is achieved using decision tree classification

#### Classification: KNN Classification

## Up to 14 neighbors KNN fitting was tested with following result

## Classification: KNN Classification



Classification: Decision Tree Classifier -> Gini-> Observation

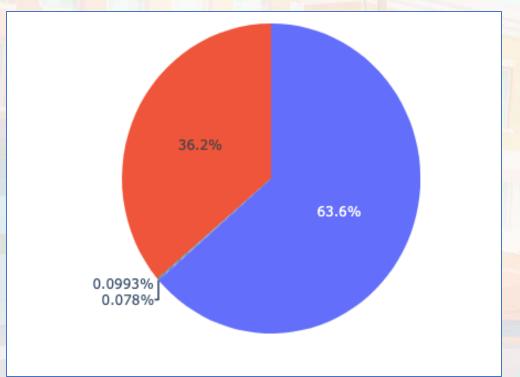
Confusion Matrix N = 3

0	90	27	0
47	86538	8816	1
30	8284	45956	62
0	35	109	5

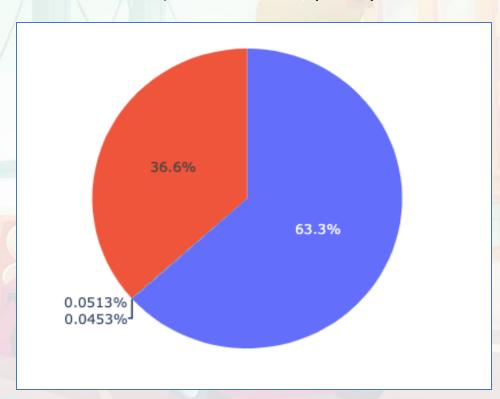
Maximum Accuracy with N = 3 (Criteria = Uniform)

## Classification: KNN Classifier -> Observation

Test Set Severity Distribution



## Classified Severity Distribution (KNN)



Classification: Conclusion

- KNN and DT both are working great for classification.
- KNN better handled continuous variables like latt. and counties code.

## **Assumption**

 Training set could be done either under/over sampling for better result

Road Accidents... Time Series Forecasting PRAMIL PAUDEL, SUMIT BHATTARAI

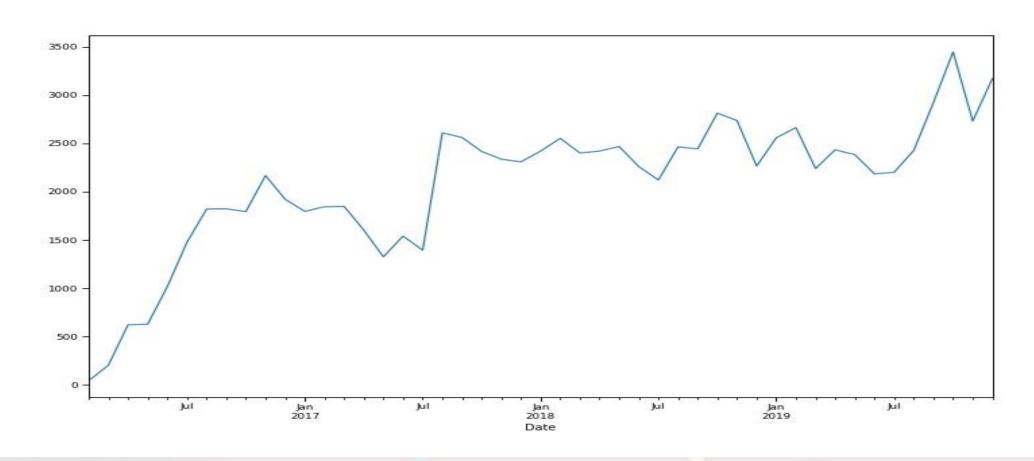
## **Data Preparation:**

- Data is prepared by taking the aggregation of count based on the Accident Start Date property for year 2016 to 2019.
- There were significant number of accident in each day.
- Data is split into 70% train and 30% test dataset.

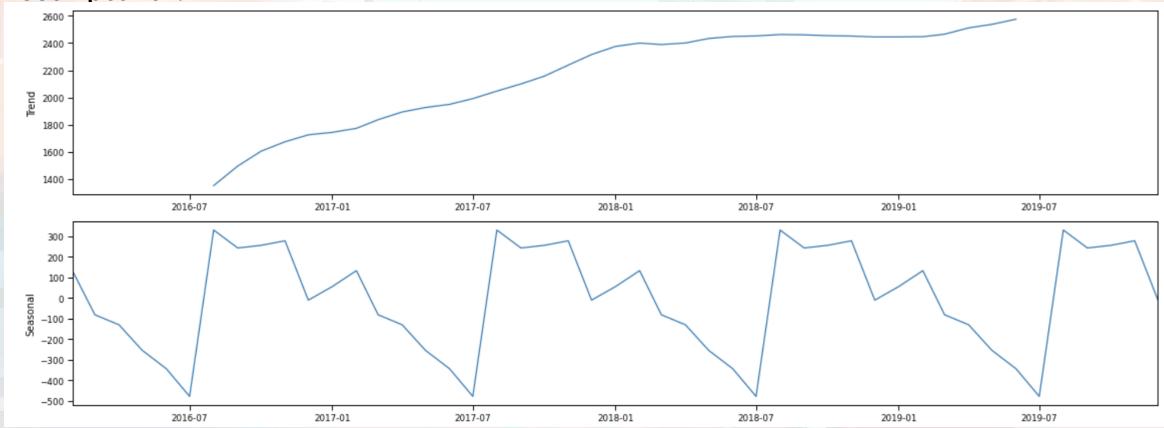
#### Procedure:

- Decomposition is used to detect the trend and seasonality of the data.
- ARIMA, SARIMAX and fbprophet are used to model the time series forecasting model.
- Grid Search is used to find the order (p,d,q) of the ARIMA model.
- Mean squared error is calculated for each p,d,q in range of (0,3) to find the order with least mean square error.
- Grid Search is used to find the parameters of SARIMAX with lowest AIC value.

## Moving Average Plot of the data:



## **Decomposition:**



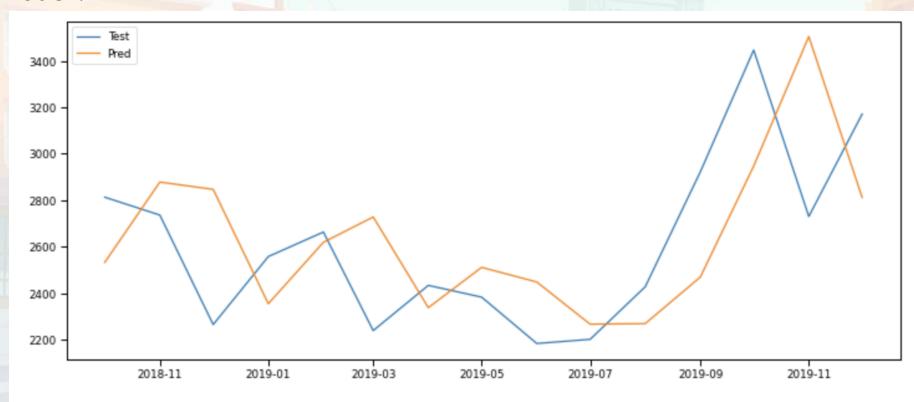
- The trend is increasing.
- There is a seasonality pattern in the data.

## **ARIMA model:**

Best (p,d,q) = (2,1,1)

		ARIMA	Model Resul	ts			
Dep. Variabl Model: Method: Date: Time: Sample:		ARIMA(2, 1,	1) Log Li mle S.D. o 020 AIC	servations: kelihood f innovatio	ns	46 -328.773 301.797 667.546 676.689 670.971	
	coef	std err	X=ROZNERONE = REE Z	P>   z	[0.025	0.975]	
ar.L2.D.ý	52.3009 0.7624 0.0526 -1.0000	0.151	3.486 5.046 0.325 -14.781 Roots	0.000 0.000 0.745 0.000	22.897 0.466 -0.264 -1.133	1.059 0.369	
	Real	Im	aginary	Modul	us	Frequency	
AR.1 AR.2 MA.1	1.2106 -15.7182 1.0000	+	0.0000j 0.0000j 0.0000j 0.0000j	1.21 15.71 1.00	82	0.0000 0.5000 0.0000	

## **ARIMA model:**



The predicted value shifts by a month.

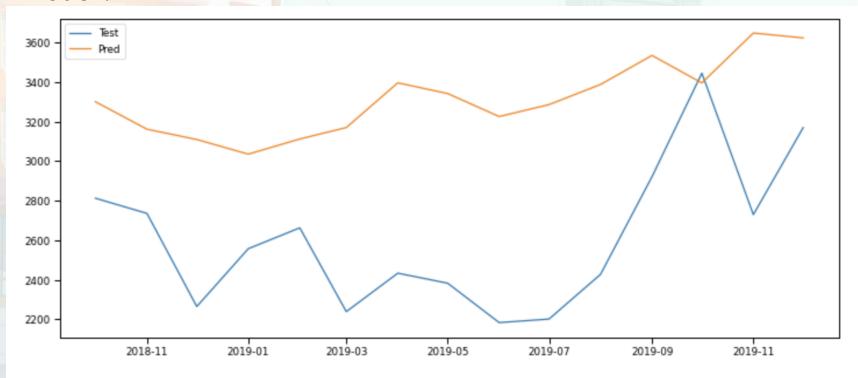
## **SARIMAX model:**

Best params:

P,d,q = (0,1,1), seasonal param = (0,1,2,7)

Dep. Varial Model: Date: Time: Sample:		IMAX(0, 1, 1		y 1, 2], 7) Nov 2020 15:14:30 0 - 47	No. Observat Log Likeliho AIC BIC HQIC			47 -284.174 576.349 583.003 578.736
Covariance	Type:			opg				
=======	coef	std err	======= Z	P> z	[0.025	0.975]		
ma.L1 ma.S.L7 ma.S.L14 sigma2	-0.0531 -0.9604 0.2800 1.089e+05	0.235		0.000 0.327	-0.414 -1.421 -0.280 5.38e+04	-0.499		
======== Ljung-Box Prob(Q): Heteroskeda Prob(H) (tv	asticity (H)		0.10 0.75 1.46 0.50	Jarque-Ber Prob(JB): Skew: Kurtosis:	=====================================	=======	6.59 0.04 0.80 4.23	

## **SARIMAX model:**

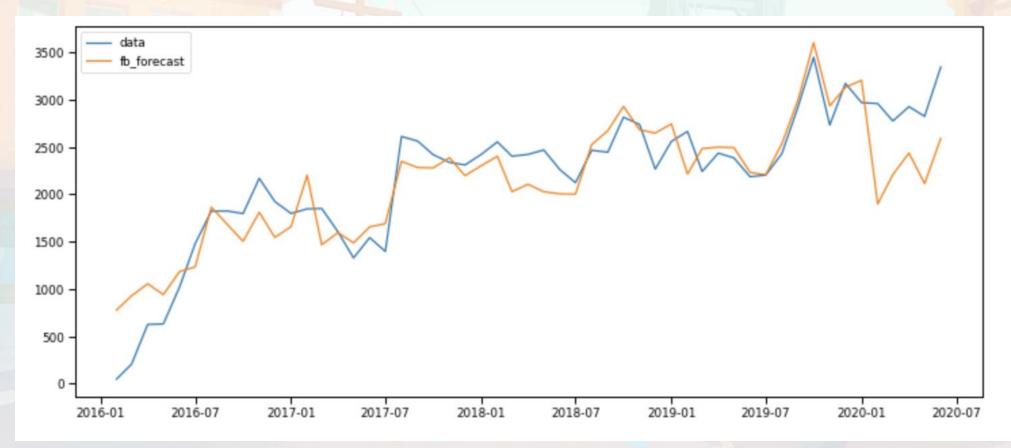


The predicted values are much higher than the expected values.

## Facebook Prophet:

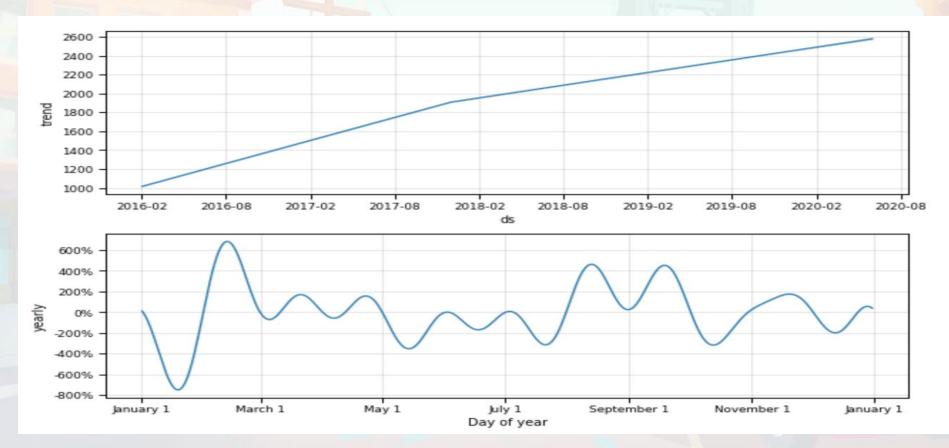


## Facebook Prophet:



- The predicted result for next six month is less than the expected value.
- The pattern of the test dataset is preserved by the model.

## Facebook Prophet:



#### Conclusion:

- ARIMA model has predicted value that is one step/month further. Some performance tuning might help.
- SARIMAX is predicting value much higher than the test value preserving some pattern.
- Facebook Prophet predicts value which is less than the actual test value and follows the test pattern. So, it seems Facebook Prophet is currently working better for this dataset.

#### References:

- •Moosavi, Sobhan, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, and Rajiv Ramnath. "<u>A Countrywide Traffic Accident</u> <u>Dataset</u>.", 2019.
- •Moosavi, Sobhan, Mohammad Hossein Samavatian, Srinivasan Parthasarathy, Radu Teodorescu, and Rajiv Ramnath.
  <u>"Accident Risk Prediction based on Heterogeneous Sparse Data: New Dataset and Insights."</u> In proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ACM, 2019.

