

# Predicting Injury in a Vehicle - Crash



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## 01. Problem Statement:

“Predicting if a crash involves an injury or not,  
and what factors lead to more crashes.”



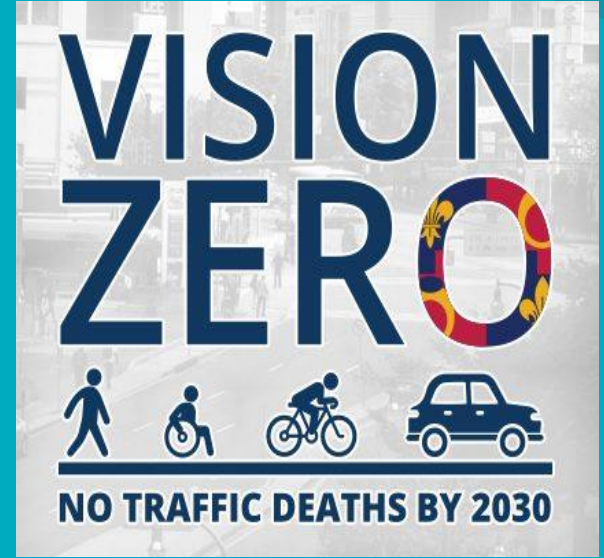
## 02. Target Audience



Automobile insurance companies like Geico, Inshur, etc.



Arizona Department of State



Programs like Vision Zero.

## 03. Brief Summary:

### Automobile Insurance Companies:

- According to The Street, liability insurance fraud is staging an accident or injury in order to deliberately file a claim against someone's insurance.
- The FBI estimates that the total cost of insurance fraud (excluding health insurance) is more than \$40 billion per year. Insurance fraud costs the average U.S. family between \$400 and \$700 per year.

### ADOT:

- Arizona Department of Transport, responsible for maintaining & constructing Arizona's highway infrastructure.

### Vision Zero:

- **Vision Zero** is a multi-national road traffic project that aims to achieve a highway system with no fatalities or serious injuries involving road traffic (Wiki).

## 04. Data Collection:

- The dataset is collected from DATA.gov .
- It consist of around 40k observations of vehicle-crash in Tempe, Arizona.
- The set contains 35 features like age of drivers, drug/alcohol use, collision manner, weather, surface condition, etc.



## 0.5 Data Cleaning

### 1st

- Filled null values

### 2nd

- Renamed columns

### 3rd

- Set 'Datetime' as the index to organize dataset

### 4rth

- Dropped useless columns

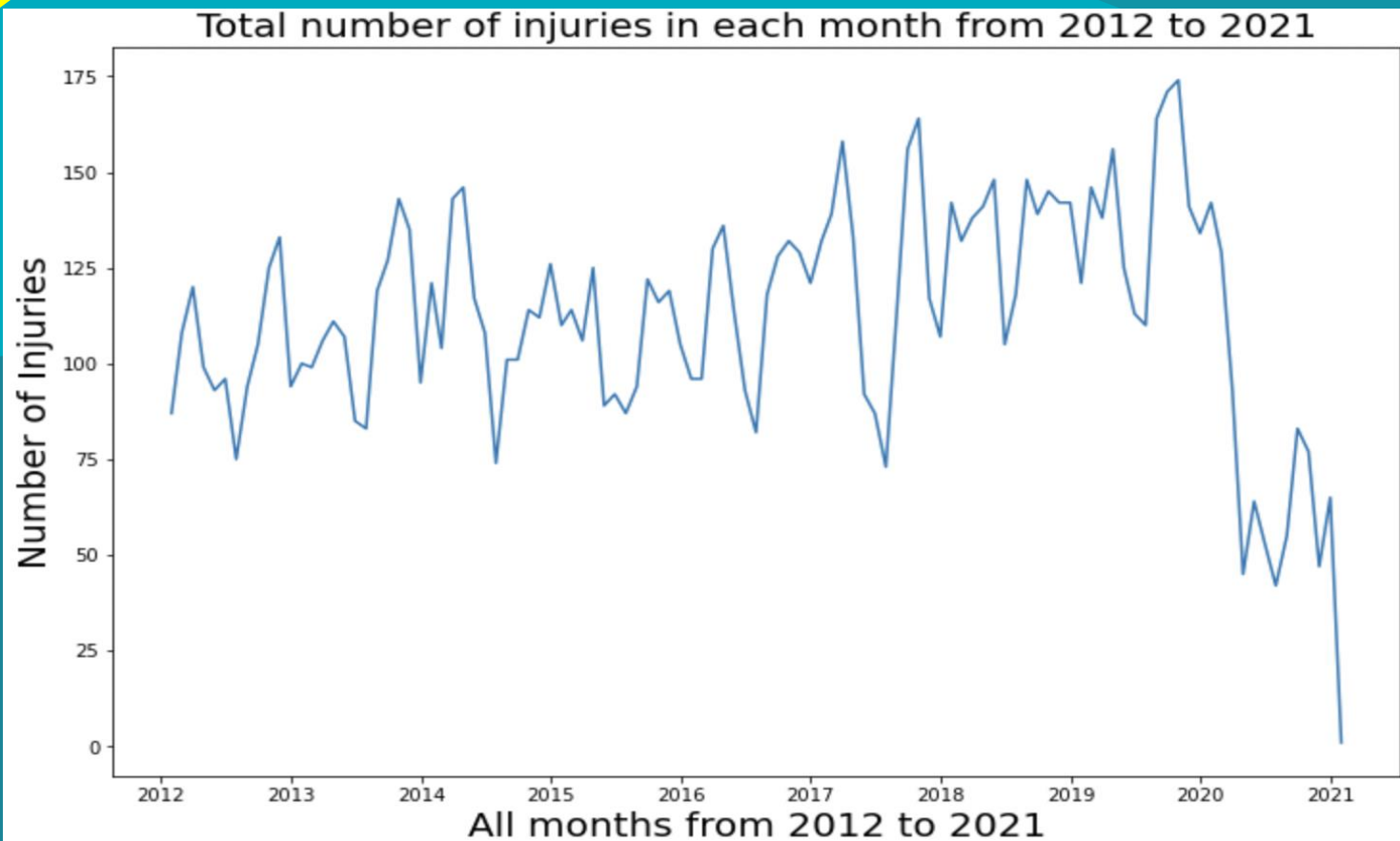
### 5th

- Used .map on many features to decrease unique values

### 6th

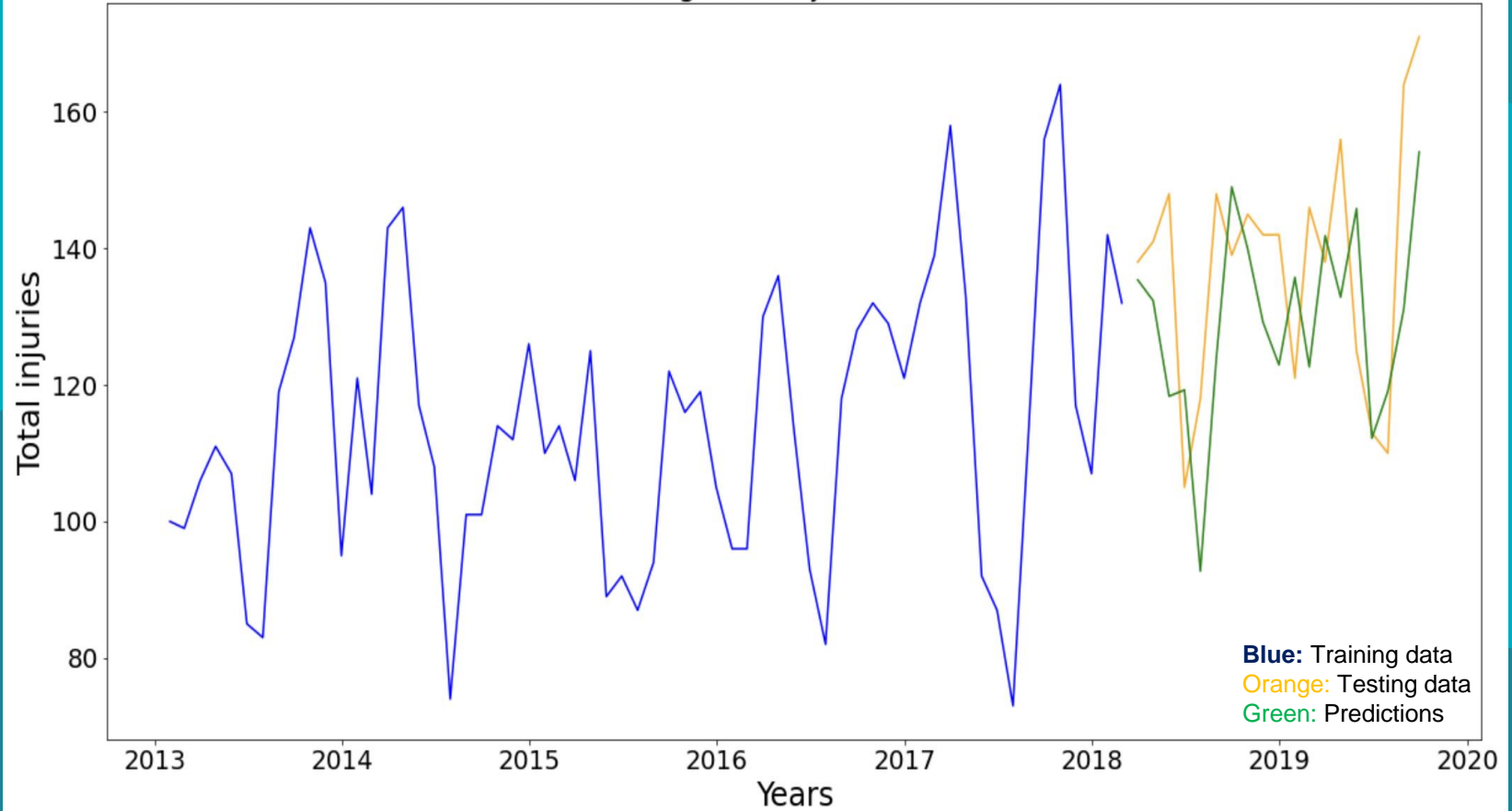
- Used dummy variables

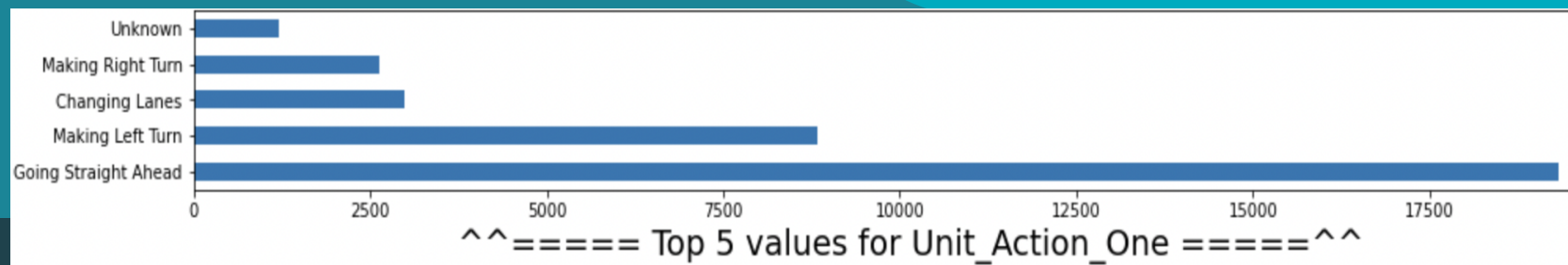
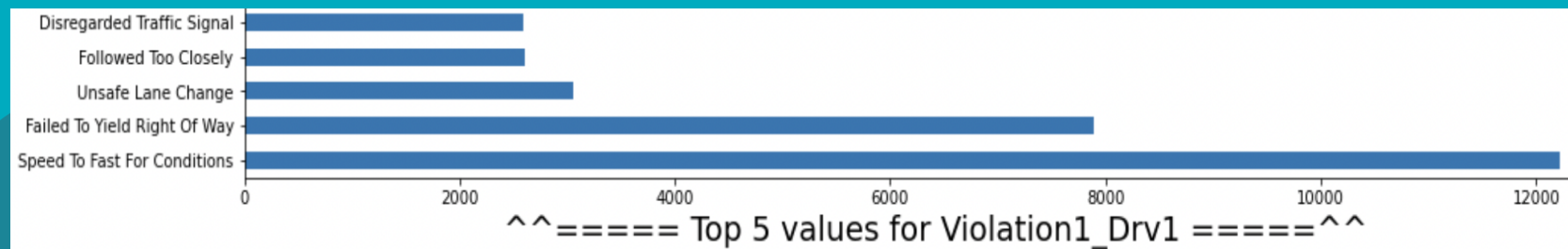
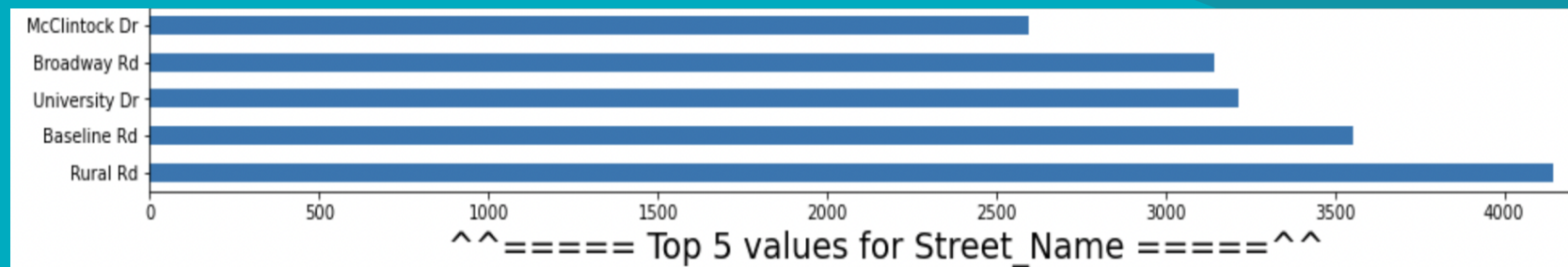
## 06.EDA:



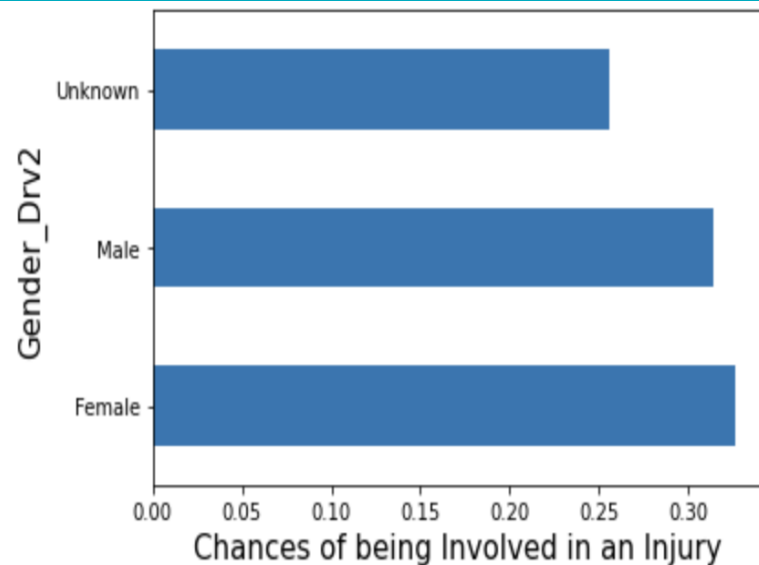
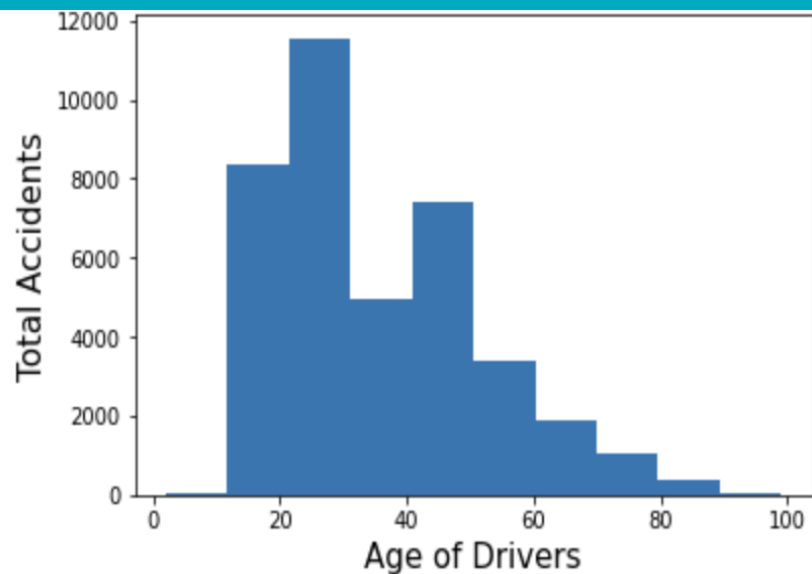
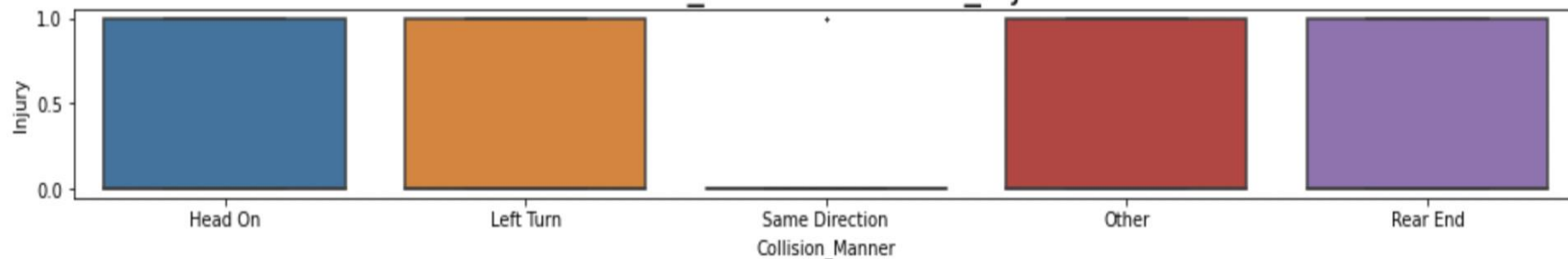


Forecasting Total Injuries 2018-2020





### Collision\_Manner vs Total\_Injuries



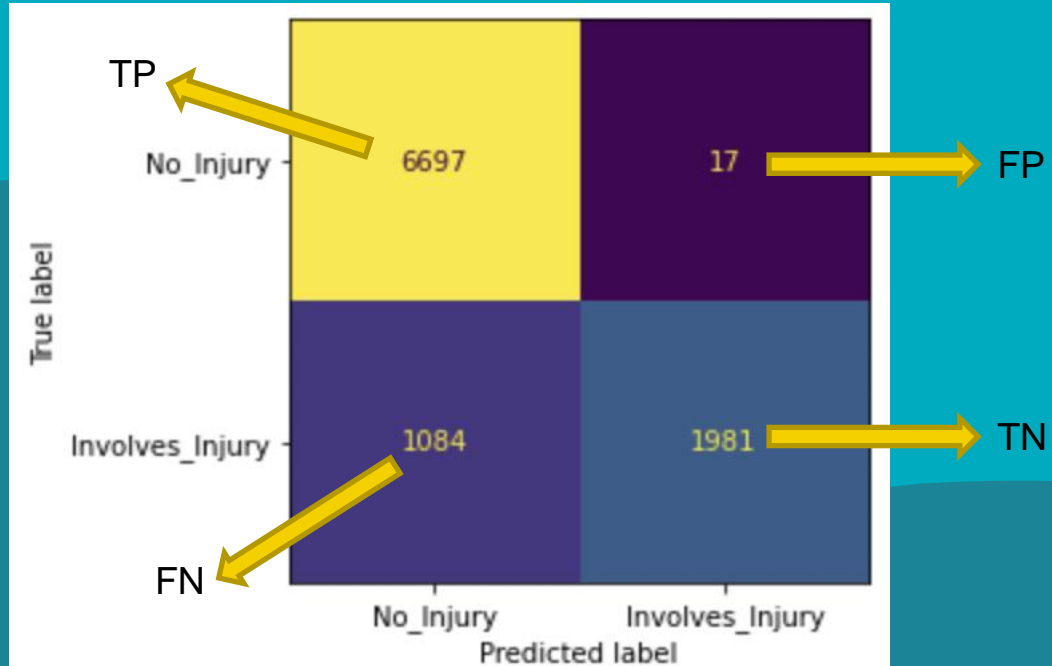
## 07. Modeling

	Model	Specificity Score
1	Logistic (GridSearch)	99.66%
2	Logistic (PCA)	99.61%
3	KNN (GridSearch)	98.36%
4	SVM	99.69%
5	Decision Tree	99.11%
6	Bagging Classifier	98.88%
7	Random Forest	98.85%
8	Extra Tree	99.05%
9	Naive Bayes (Bernoulli)	99.74%
10	<b>ADA Boosting</b>	<b>99.75%</b>
11	Neural Netork (NN)	99.67%

Baseline Score = 69%

Best Score

$$\text{Specificity} = \frac{\text{True Negatives (TN)}}{\text{True Negatives (TN)} + \text{False Positives (FP)}}$$



## 08.a Conclusions:

- EDA graphs.
- Top positive correlated features to Injury: Alcohol\_Use, Drug\_Use, Injury\_Severity.
- Top negative correlated features: Age\_Drv, Surface condition, weather.
- Most of the collisions were vehicle to vehicle, very few crash reports on the vehicle to pedestrian/bicycle.
- Best Model: Ada Boosting (highest specificity score 99.75%).

## 08.b Recommendations:

- Higher fines/points on traffic violations (Alcohol, Drug).
- Installing video cameras at the top 5 streets and intersections where most accidents happened.
- Free driving lessons at any time.
- Requiring people to renew license every year and compulsory taking lessons to renew it.
- Our ADA Boosting can be used by automobile insurance companies to check for false injury claims.
- With all the above steps, we can help the Arizona Department of Transportation (ADOT) minimize crashes and contribute to the Vision Zero initiative.



## 09. Streamlit App



# THANK YOU!

# ANY QUESTIONS?

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