



# STAT 632: Regression Analysis

## Predicting Road Accident Severity in the US (2016-2023) : A Multiple Linear Regression and Random Forest Analysis

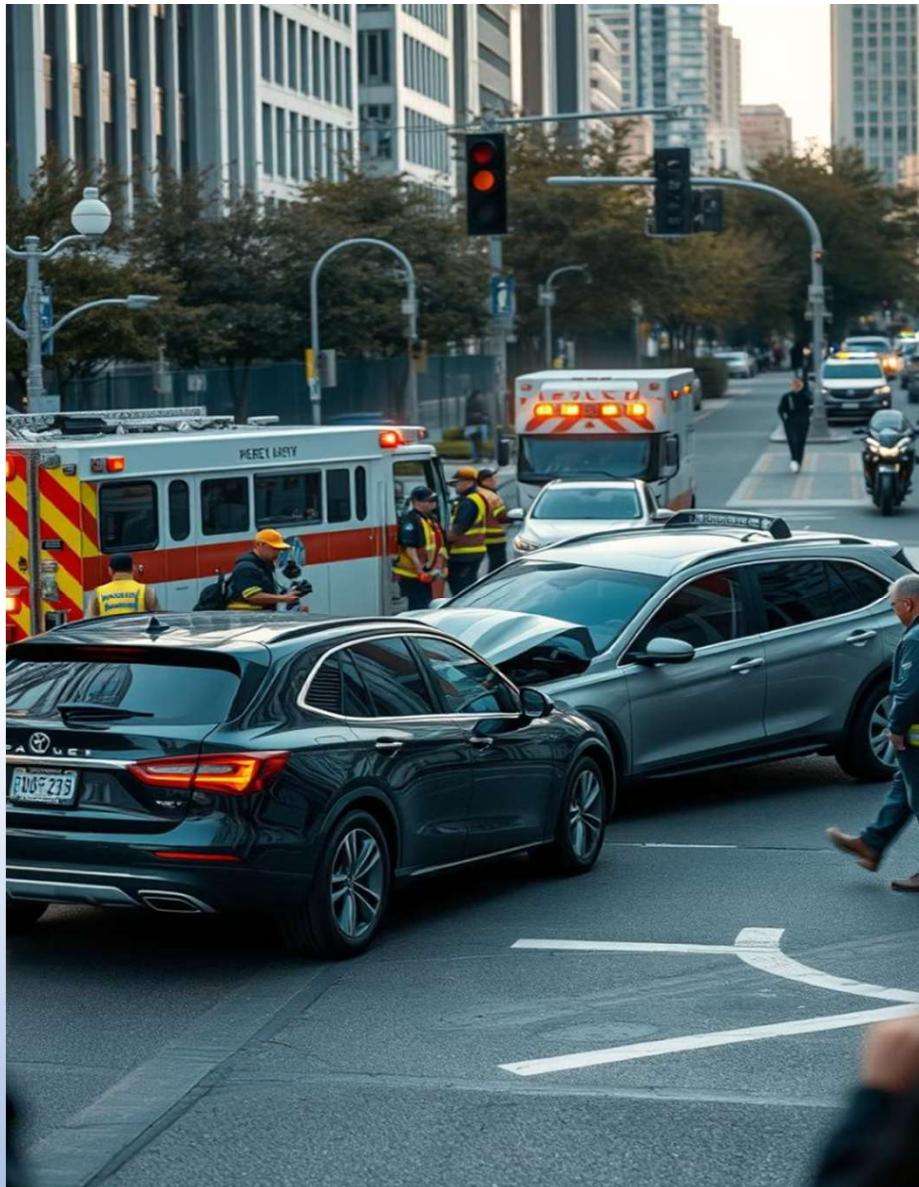
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# Agenda

1. Introduction & Motivation
2. Project Goal & Research Questions
3. Dataset Overview
4. Data Preprocessing & EDA
5. Modeling Approaches
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  - ❖ Logistic Regression
  - ❖ Random Forest Classification
6. Model Evaluation
7. Key Results & Interpretation
8. Conclusion & Future Work





# Project Goal & Research Question:

## Project Goal

To analyze patterns in road accidents across the United States from 2016 to 2023 using regression models. The aim is to **predict accident severity** and identify the most influential factors contributing to severe outcomes.

## Research Questions

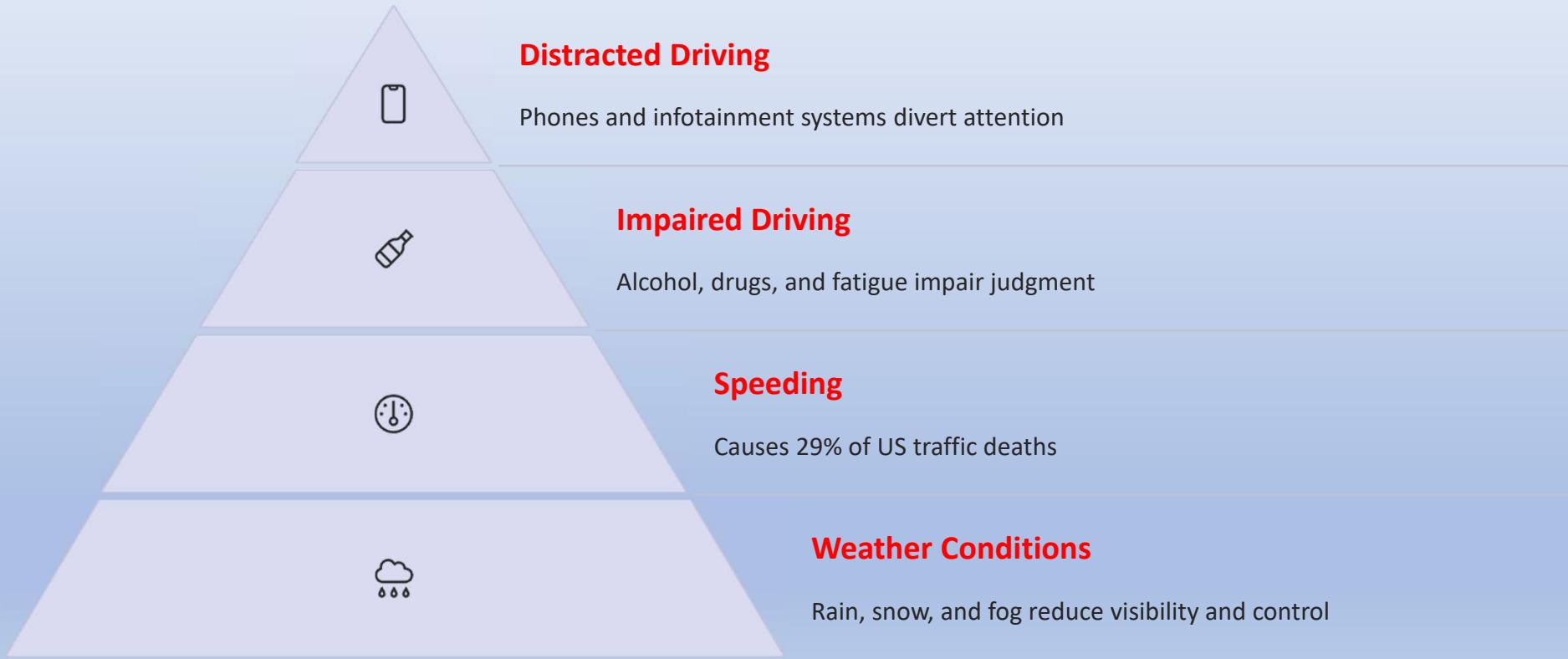
- What are the key predictors of road accident severity in the US?
- How do environmental and temporal factors (e.g., weather, visibility, time of day) influence the severity of road accidents?
- Can Multi-linear regression and Random forest models accurately classify and predict accident severity?



## Dataset Overview

- Source: Kaggle – U.S. Accidents (2016-2023)
- Data size: 7.7 Million entries, 46 total columns
- Sample Size: 50,000 rows
- Target Variable: Severity (1 to 4)
- Key Predictors: Weather: temperature, rain, fog, State etc.
- Road Features: Bump, junction, traffic signal etc..
- Time: Peak hour, weekend

# Common Causes of Car Accidents



# Multiple Linear Regression

## MLR Full Model Results:

```
Call:
lm(formula = Severity ~ Distance + Temperature + Humidity + Visibility +
    Wind_Speed + Pressure + Precipitation + Weather_Simple +
    Rush_Hour + Weekend + Is_Daylight + Traffic_Signal_Flag +
    Road_Features + State, data = accident_data)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.4874	-0.1975	-0.1052	-0.0492	2.1603

### Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.8178716	0.0828328	21.946	< 2e-16 ***
Distance	0.0021842	0.0006904	3.164	0.001559 **
Temperature	0.0009606	0.0001185	8.109	5.18e-16 ***
Humidity	0.0002248	0.0001035	2.172	0.029839 *
Visibility	-0.0005650	0.0009724	-0.581	0.561267
Wind_Speed	0.0006393	0.0003521	1.816	0.069426 .
Pressure	0.0108640	0.0027150	4.001	6.30e-05 ***
Precipitation	0.0399863	0.0161080	2.482	0.013053 *
Weather_SimpleCloudy	0.0183983	0.0039791	4.624	3.77e-06 ***
Weather_SimpleFreezing	0.2788720	0.0598741	4.658	3.20e-06 ***
Weather_SimpleRainy	0.0761174	0.0077852	9.777	< 2e-16 ***
Weather_SimpleSnowy	0.0389131	0.0130372	2.985	0.002839 **
Rush_Hour	-0.0064177	0.0037293	-1.721	0.085277 .
Weekend	0.0393409	0.0045397	8.666	< 2e-16 ***
Is_Daylight	-0.0085665	0.0042549	-2.013	0.044085 *
Traffic_Signal_Flag	-0.1048751	0.0053955	-19.438	< 2e-16 ***
Road_Features	-0.0417544	0.0044502	-9.383	< 2e-16 ***
StateAR	0.0731888	0.0315940	2.317	0.020532 *
StateAZ	-0.1388048	0.0191841	-7.235	4.69e-13 ***
StateCA	-0.1242984	0.0146645	-8.476	< 2e-16 ***

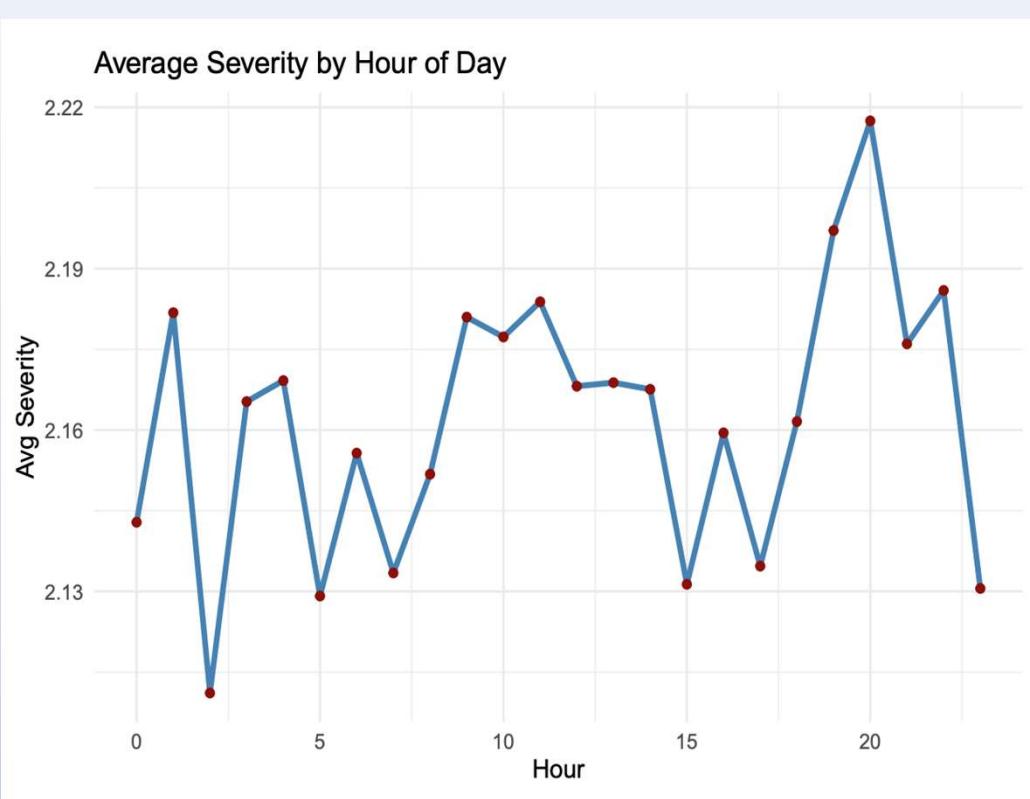
## Reduced model Results

	##	## Coefficients:	Estimate	Std. Error	t value	Pr(> t )
## (Intercept)	1.9660903	0.0297308	66.130	< 2e-16	***	
## Distance	-0.0031206	0.0026210	-1.191	0.233822		
## Temperature	0.0011373	0.0002505	4.540	5.68e-06	***	
## Humidity	0.0004753	0.0002080	2.286	0.022294 *		
## Wind_Speed	0.0001377	0.0007332	0.188	0.851003		
## Weather_SimpleCloudy	0.0090643	0.0081249	1.116	0.264603		
## Weather_SimpleFreezing	0.1208959	0.1103757	1.095	0.273399		
## Weather_SimpleRainy	0.0786488	0.0147898	5.318	1.07e-07 ***		
## Weekend	0.0376573	0.0092539	4.069	4.74e-05 ***		
## Traffic_Signal_Flag	-0.1089508	0.0113773	-9.576	< 2e-16 ***		
## Road_Features	-0.0393543	0.0090081	-4.369	1.26e-05 ***		
## StateCA	0.0279006	0.0211715	1.318	0.187580		
## StateCO	0.3702451	0.0341941	10.828	< 2e-16 ***		
## StateFL	0.0146901	0.0227501	0.646	0.518474		
## StateGA	0.3315951	0.0301842	10.986	< 2e-16 ***		
## StateIA	0.3494500	0.0569610	6.135	8.76e-10 ***		
## StateIL	0.3486123	0.0299254	11.649	< 2e-16 ***		
## StateIN	0.3549783	0.0405513	8.754	< 2e-16 ***		
## StateKY	0.2894248	0.0494526	5.853	4.95e-09 ***		
## StateLA	0.0257535	0.0287378	0.896	0.370188		
## StateMA	0.2094755	0.0439204	4.769	1.87e-06 ***		
## StateME	0.0631046	0.1460898	0.432	0.665779		
## StateMI	0.1395208	0.0311093	4.485	7.36e-06 ***		
## StateMN	0.0424529	0.0289212	1.468	0.142160		
## StateMO	0.3225876	0.0366880	8.793	< 2e-16 ***		
## StateMT	0.0164094	0.0543041	0.302	0.762522		
## StateNC	0.0953699	0.0247546	3.853	0.000117 ***		
## StateNH	0.0964838	0.1154056	0.836	0.403147		
## StateNM	0.3646688	0.0749817	4.863	1.17e-06 ***		
## StateOH	0.1875112	0.0328704	5.705	1.19e-08 ***		
## StateOK	0.0117528	0.0367951	0.319	0.749419		
## StateOR	0.0354479	0.0281422	1.260	0.207835		
## StateRI	0.3924769	0.0658177	5.963	2.54e-09 ***		
## StateSC	0.0036847	0.0242074	0.152	0.879021		
## StateWA	0.2502880	0.0333549	7.504	6.59e-14 ***		
## StateWI	0.3794455	0.0471177	8.053	8.75e-16 ***		
## StateWV	0.0079154	0.0687329	0.115	0.908318		
## StateWY	0.0705615	0.1461711	0.483	0.629294		

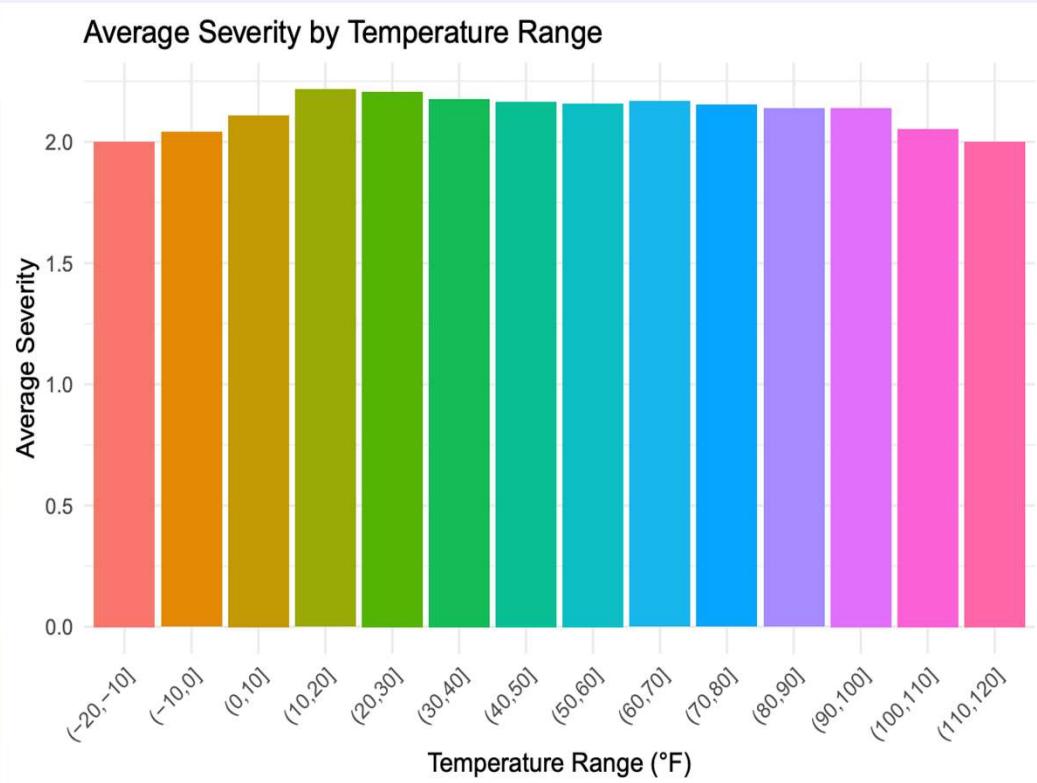
- Adjusted  $R^2 = 0.060 \rightarrow$  Model explains ~6% of variance in severity
- F-statistic = 21.08,  $p < 0.05 \rightarrow$  Model is statistically significant
- Residual standard error = 0.4379 (indicates moderate prediction error)

- The reduced model has better explanatory power (Adjusted  $R^2 = 7.8\%$  vs. 6.0%)
- It also has lower residual error, indicating tighter model fit
- Unnecessary or insignificant predictors were removed — improving model simplicity and interpretability
- Focuses only on important weather types and states
- Avoids multicollinearity, as shown by improved VIF scores

## Trend of average severity by hour:



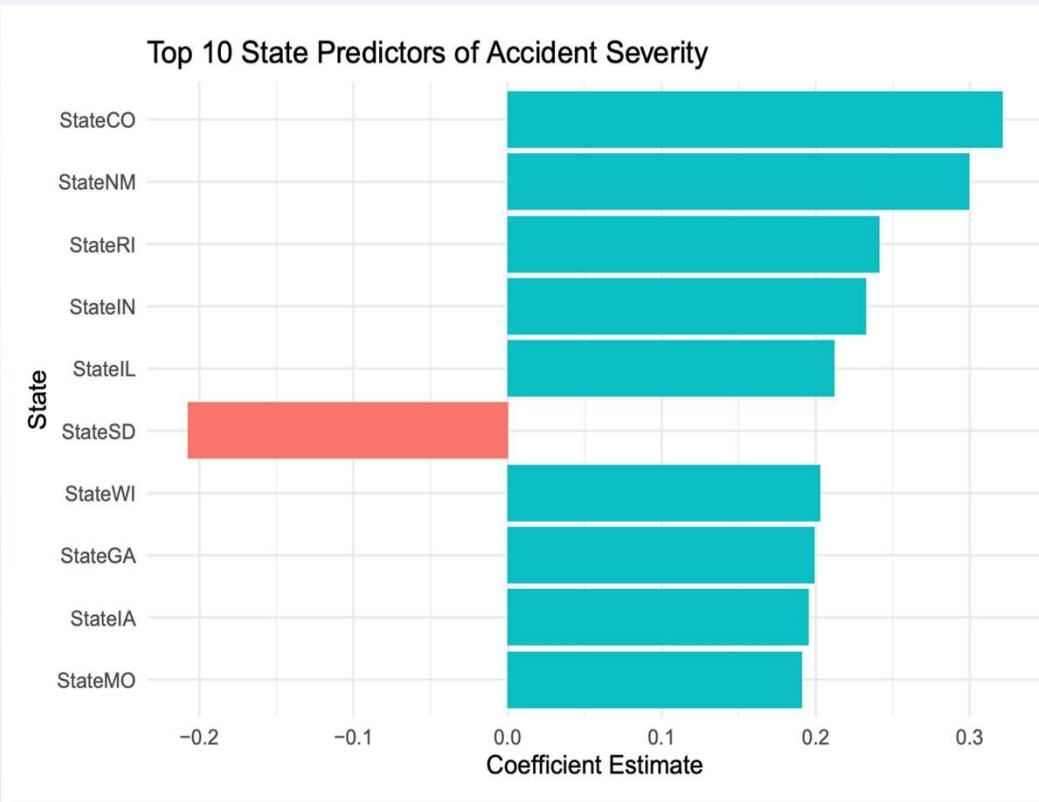
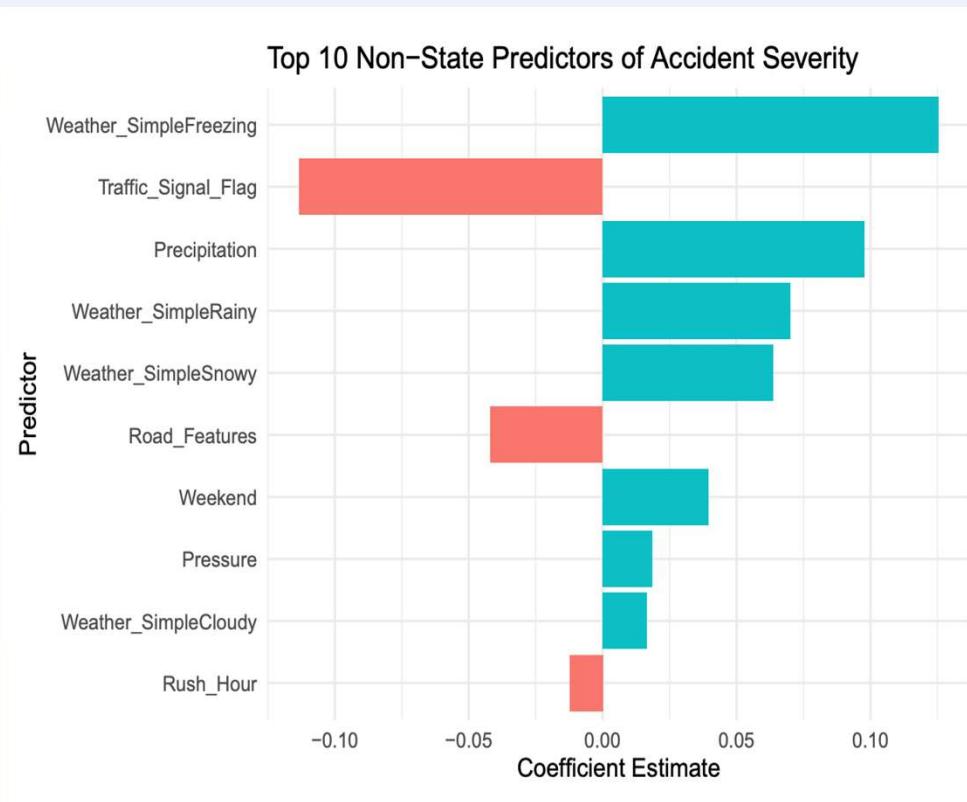
## Average Severity by Temperature Range:



- Shows **average accident severity** for each hour (0 to 23)
- Severity fluctuates throughout the day, mostly ranging between **2.13 and 2.22**
- **Highest average severity occurs between 7 PM and 9 PM**
- **Lowest severity appears around early morning (2–4 AM) and mid-afternoon (3–5 PM)**
- No clear peak during traditional **rush hours** (7–9 AM and 4–6 PM)

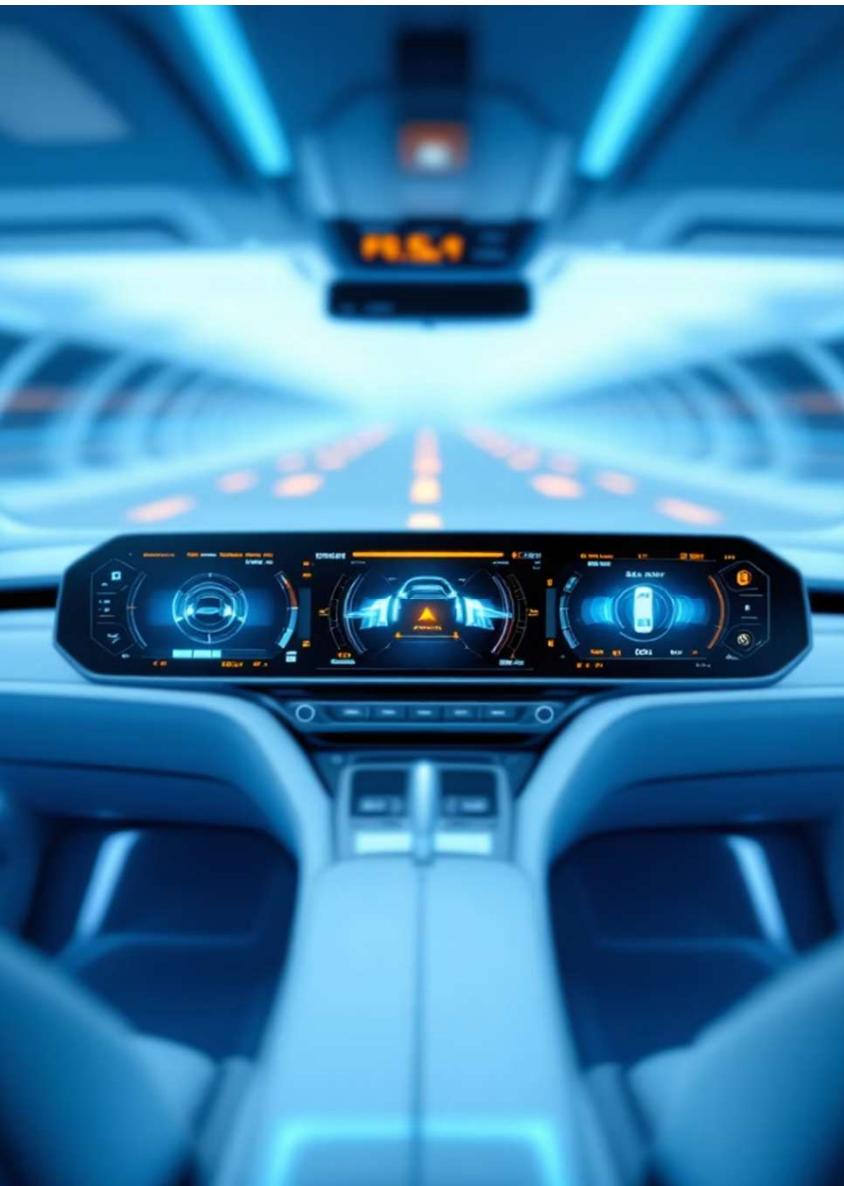
- Severity peaks in the **20°F to 30°F** range
- Temperatures **below freezing and above 100°F** are associated with **lower average severity**
- Overall, **mid-range temperatures (20–60°F)** show the highest average severity
- Severity gradually declines after ~**60°F**

## Bar plot of model coefficients:

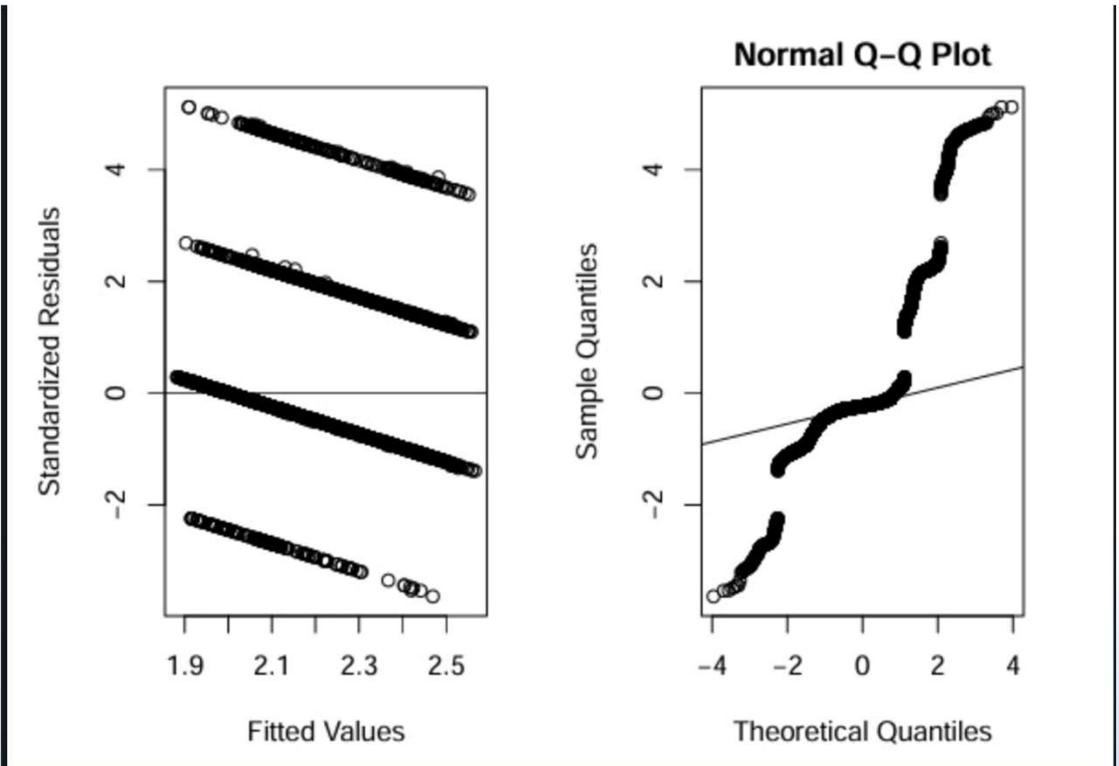


- Weather Freezing and Precipitation have the strongest positive effects on severity
- Traffic Signal Flag and Road Features show **negative effects**, meaning their presence reduces severity
- Rainy and Snowy weather both increase severity, with Rainy having a stronger impact
- Weekend accidents are slightly more severe on average
- Pressure and Cloudy conditions also contribute, but to a lesser extent
- Rush Hour appears to slightly reduce severity (possibly due to congestion reducing speed)

- Colorado (CO) shows the **highest positive effect** on accident severity
- New Mexico (NM), Rhode Island (RI), Indiana (IN), and Illinois (IL) also show significantly higher severity
- South Dakota (SD) is the only state in this list with a **negative effect**, indicating lower average severity
- Differences reflect **regional driving behavior, infrastructure, enforcement, or reporting standards**
- State effects capture variability not explained by weather or road features alone



## Diagnostics for reduced model



- **Residuals vs. Fitted Plot**
- Residuals form **distinct horizontal bands**, indicating discrete response levels (Severity = 1 to 4)
- No obvious **fan shape** or severe heteroscedasticity
- Pattern reflects the **ordinal nature** of the response variable rather than violation of assumptions

- **Q-Q Plot**
- Deviations from the diagonal line at both ends
- Suggests **non-normality** in residuals
- Caused by the **discrete structure** of the response, not by poor model fit

# Random Forest model & Variable importance from Random Forest

Call:

```
randomForest(formula = Severity ~ Distance + Temperature + Humidity + Visibility + Wind_Speed + Pressure + Precipitation + Weather_Simple + Rush_Hour + Weekend + Is_Daylight + Traffic_Signal_Flag + Road_Features + State, data = rf_data, ntree = 800, importance = TRUE)
```

Type of random forest: classification

Number of trees: 800

No. of variables tried at each split: 3

OOB estimate of error rate: 14.48%

Confusion matrix:

	1	2	3	4	class.error
1	23	382	14	0	0.94510740
2	8	27659	380	6	0.01404484
3	0	3232	741	0	0.81349106
4	0	784	6	4	0.99496222

[1] "Overall Accuracy: 85.52 %"

Variable Importance (Random Forest)

Distance  
State  
Traffic\_Signal\_Flag  
Temperature  
Humidity  
Pressure  
Weekend  
Visibility  
Weather\_Simple  
Precipitation  
Road\_Features  
Is\_Daylight  
Wind\_Speed  
Rush\_Hour

MeanDecreaseAccuracy

Distance  
State  
Pressure  
Temperature  
Humidity  
Wind\_Speed  
Visibility  
Weather\_Simple  
Traffic\_Signal\_Flag  
Weekend  
Precipitation  
Rush\_Hour  
Road\_Features  
Is\_Daylight

MeanDecreaseGini

"Overall Accuracy: 85.52 %"

- Top predictors: Distance, State, Traffic Signal, Pressure
- Distance is the most important feature across both metrics
- State also highly influential — reflects geographic variation in severity
- Traffic Signal Flag has a clear role: accidents with signals tend to be less severe
- Weather and visibility play a moderate role
- Peak Hour and Road Features are less important in the model

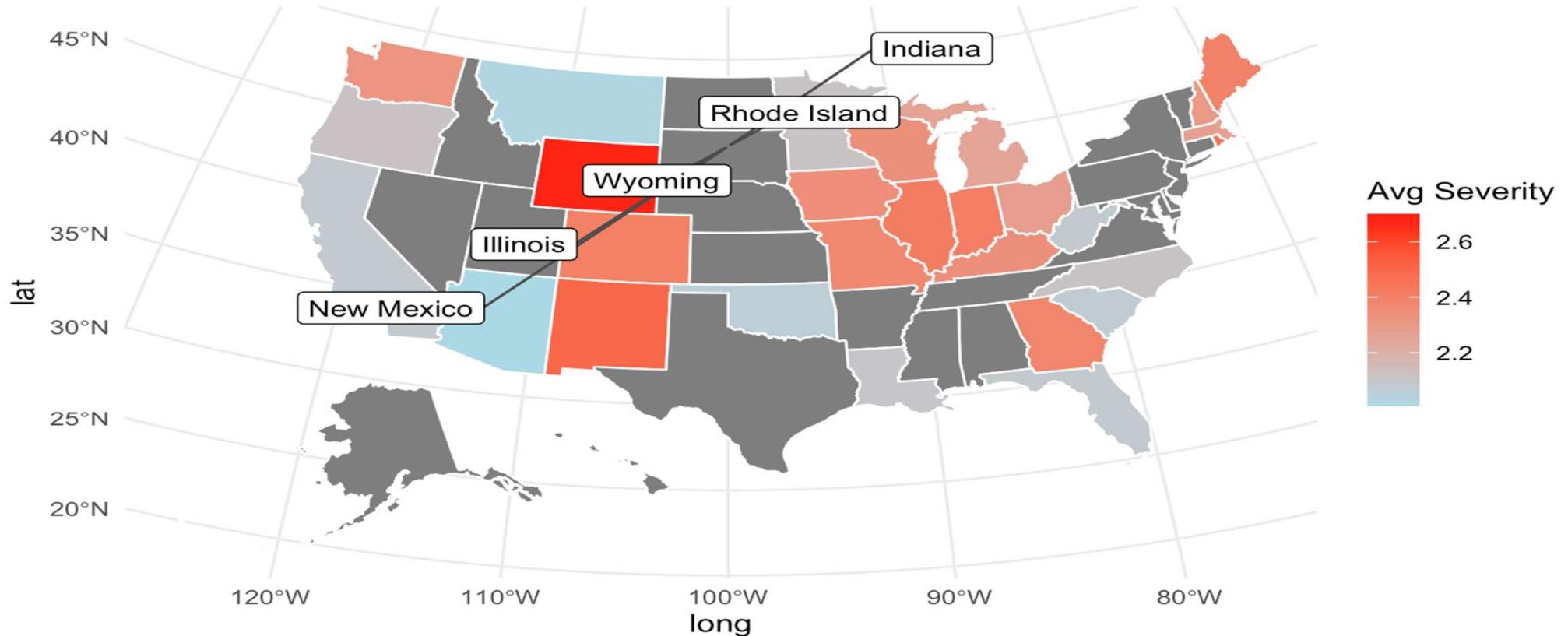


## Confusion matrix heatmap (Random Forest)



- The confusion matrix shows that the Random Forest model is highly accurate for the majority class (Severity = 2), but performs poorly on rare classes like Severity = 1 and 4.
- This imbalance skews predictions and suggests the need for class rebalancing (e.g., SMOTE, downsampling, or weighting) to improve generalization to all severity levels.

## Top 5 States by Average Accident Severity



- Highlighted states: Wyoming, Illinois, New Mexico, Rhode Island, Indiana
- These states have the **highest average severity** across all crashes in the dataset
- Severity ranges from ~2.4 to 2.65, with red indicating more severe crashes
- Patterns suggest possible **regional effects** beyond weather and road conditions
- Could reflect differences in **driving behavior, road design, enforcement, or reporting practices**

# Conclusion:

- Linear models helped us interpret relationships, while random forest gave us better accuracy.
- For future work, we'd like to improve prediction for rare severity levels and include more time-based seasonal features.





THANK YOU  
DRIVE SAFE.

*“Every accident is a lesson. Let’s  
learn and prevent.”*