Project Midterm Report

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Introduction

While car accidents cause safety issues for citizens, this project aims to focus on the economic impacts; in other words, we want to predict accidents' impact on the traffic. Our data set consists of 47 features and 1,516,064 data records. Each record represents a car accident in the US during 2016 to 2020. The variable of interest is 'accident severity' (on the traffic), which has been previously encoded from 1 to 4 with 4 being the most severe. The independent variables mainly contain 4 aspects, including locations, timings, weathers, and traffic conditions. They also have 3 major data types: continuous values (int/float), categorical(object/bool), text (object) shown in TABLE 1.

No Missing Values	
Give_Way, Turning_Loop, Traffic_Signal, Traffic_Calming, Stop, Station, Roundabout, Railway, No_Exit, Junction, Crossing, Bump, Amenity	bool
Start_Lat, Start_Lng, End_Lat, End_Lng, Distance(mi), Severity	float64 & int
Country, Start_Time, End_Time, State, Description, Street, Side, County, ID	object

TABLE 1: All Feature Types and Missing Value Info

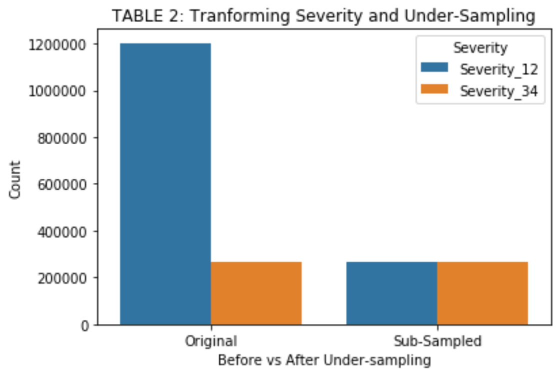
	Missing Percentage	Missing Amount	Data Type
Number	0.690007	1046095	float64
Precipitation(in)	0.33676	510549	float64
Wind_Chill(F)	0.29637	449316	float64
Wind_Speed(mph)	0.084998	128862	float64
Humidity(%)	0.030018	45509	float64
Visibility(mi)	0.029162	44211	float64
Weather_Condition	0.029027	44007	object
Temperature(F)	0.028385	43033	float64
Wind_Direction	0.02761	41858	object
Pressure(in)	0.023926	36274	float64
Weather_Timestamp	0.019962	30264	object
Airport_Code	0.002802	4248	object
Timezone	0.001518	2302	object
Zipcode	0.000617	935	object
Sunrise_Sunset	0.000055	83	object
Civil_Twilight	0.000055	83	object
Nautical_Twilight	0.000055	83	object
Astronomical_Twilight	0.000055	83	object
City	0.000055	83	object

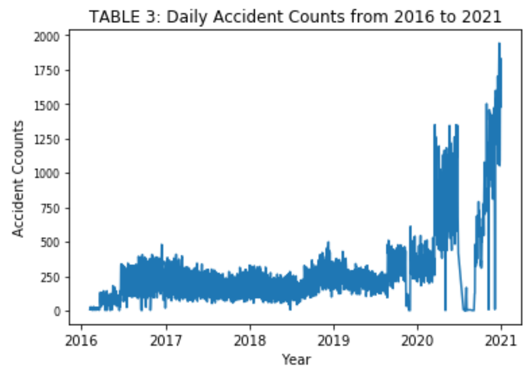
Table 1 shows all features with missing values and percentage of missing. 19 out of 47 features contain missing values and the majority is missing less than 10%. We divided these features into 4 types and treated them differently. First, the top 3 features are missing far too many values, 60% and 30% (compared to less than 10% missing in other features). Imputation would be less accurate and affect data integrity, so we decided to drop them. Second, the last 8 features only miss less than 5000 entries (<0.5%), so we simply dropped the missing rows. Third, the rest of the features are missing about 1% each and are all weather features. We will impute them with data in the same county during the same 2-week period. Categorical features such as 'weather_condition' will be imputed by the most common category in that period and real-value features will be imputed by the median of the period.

2. Cleaning, Exploring, and Engineering the Features

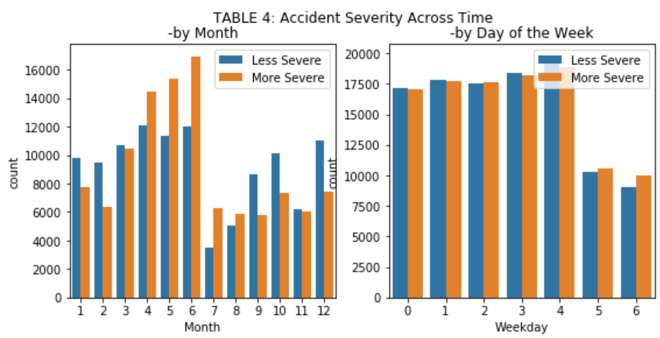
We cleaned data format in each feature and conducted exploratory analysis to find insights. Based on the insights, we further cleaned outliers, transformed data into new features, or engineered additional encoding. In the end, we dropped features we believed were meaningless or unable to include in the model. Below, we will introduce a few features that required substantial engineering and yielded significant insights.

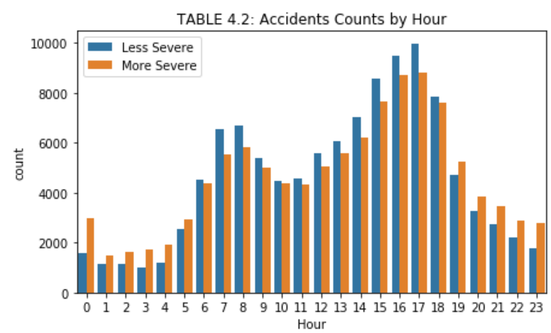
Severity (Dependent Variable): has four values from 1 to 4. The challenge is that there is no knowledge of how the levels are defined and only 1% of total data has a severity level of 1. Therefore, we transformed severity into a binary categorical feature by combining level 1 and 2 into 'less severe' and 3 and 4 into 'more severe'. However, from TABLE 2, there was still a serious imbalance between the two classes, so we performed a random under-sampling on the majority class ('less severe'), retaining a balanced data set where the two labels weigh equally.





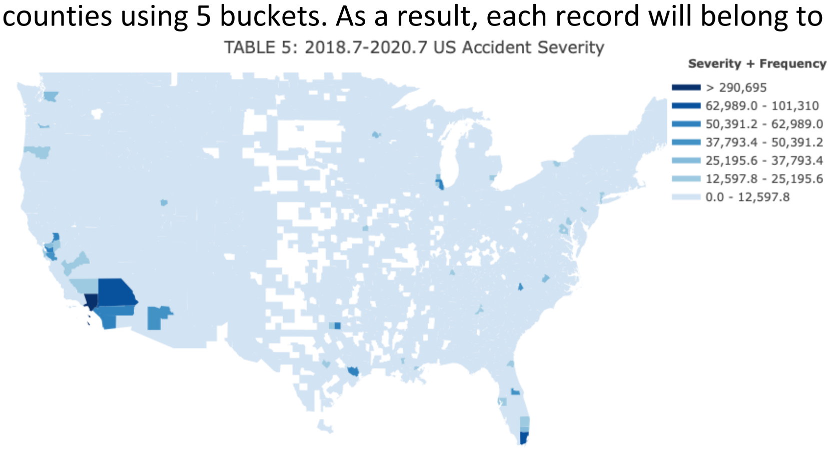
Time: After converting the feature into 'datetime' format, we plotted the number of accidents in the past 4 years. From TABLE 3, we observed an unexpected dip of records during July 2020, a sharp increase and great volatility thereafter. To retain stable, sufficient and recent data, we decided to keep data only from 2018-07-01 to 2020-07-01. Second, even though we observed cyclicality in the data, accidents are not naturally determined by date and people are more interested in learning causes due to weather and location. Therefore, this is not a time series prediction and we will only incorporate date information in terms of the year, month, week, day of the week, and time of the day (by creating these new features).

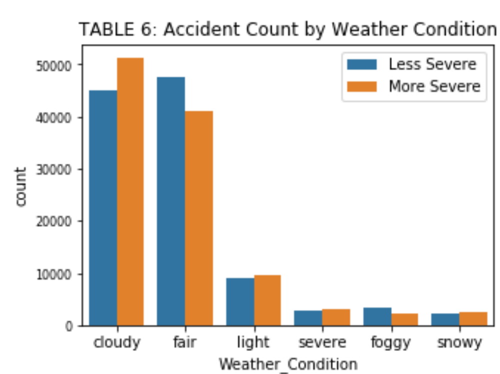




From TABLE 4 we observed that compared to other seasons, winter has more accidents but less severe ones, possibly because there is more precipitation then, but people are more cautious. Moreover, there are more accidents on weekdays, but weekends tend to have more severe cases. Similarly, there are more accidents during rush hours but more severe ones at night. Last, we removed some Boolean features which produced almost identical insights.

County: includes 1671 unique counties in the US. We first join our dataset with an external county indices table and observed accident severity and frequencies in the following map (TABLE 5). We can clearly notice that accident distributions are extremely skewed to the right. Even among the top 3 counties, Los Angeles County has 3 times more accidents than Miami County and 5 times than San Bernardino, which is only a 30-minute drive away from LA. Counties in Texas and Illinois have the highest severity. The rest all have equally low frequency or severity. Therefore, we created 5 buckets based on the frequency of the more severe accidents and encoded the counties using 5 buckets. As a result, each record will belong to a county_severity_level from 1 to 5.





Weather: One major weather indicator is 'weather_condition', a categorical feature with 117 labels. We first applied text manipulation to sort the labels into 6 groups (in TABLE 6). Accidents in general are more likely to happen in cloudy days and moderate weathers, maybe because that less people are inclined to go out during severe weathers. Weathers with precipitation (cloudy, light rain, severe storms, snowy) have more severe cases. Since all six categories showed variation and reasonable insights, we kept them all. We did a similar text manipulation with 'wind_direction' and removed features that produced not workable insights.

Street Locations: contain 93,048 unique values of actual street names. We extracted 20 most frequent ones (e.g., US-, Interstate-) through text manipulation, created a dummy variable for each, and compared the correlation of the labels with accident severity. Although we did not gain significant insights on the current sub-sampled data set, we plan to apply this approach on future samples and modifications.

3. Fitting and Interpreting Models

We first applied 3 methods to improve model fit. We implemented one-hot encoding to convert categorical features into binary ones, obtaining 27 features. We then scaled and standardized the data. And last, we split the data into training and testing data set by an 8-2 ratio.

TABLE 7: Sample Model Performance

	precision	recall	f1-score	support
0	0.73	0.68	0.71	22116
1	0.7	0.75	0.72	21884
Testing:	0.72	0.71	0.71	44000
Training:	0.71	0.71	0.71	176000

In fitting a logistic regression model, we used a grid search to find the best hyperparameters and regularization method. The best model used L2 regularization and had an overall accuracy of 0.72. From TABLE 7, we see that training and testing errors are similar, and that the error metrics give similar results, suggesting that we managed to avoid overfitting. However, we think the accuracy is not high enough for us to gain insights from this model (e.g., interpreting p-values). We aim to further improve model performances in the next steps.

4. Key Considerations

In order to prevent overfitting and underfitting, we retained sufficient data points (220000) and obtained only 27 relevant features. We removed missing values to prevent sparsity, and reduced categories in some features to decrease total features in the model. We also plan to use ensemble learning methods to prevent underfitting. Additionally, to test model effectiveness (and prevent overfitting), we split the data into training and testing set, and plan to apply cross validation. Regularization is also used in logistic regression model that we fit. Last, to choose the best features to use, we first examined the variation and insight in each feature, and selected the features that are sufficiently correlated with 'severity' from a correlation heatmap.

5. Next Steps

We first plan to fit more models using the current sample data set, especially boosting and bagging methods, which and prevent over- or under-fitting and produce feature importance rankings. Then, we will further engineer features and resample the data. If necessary, we may try to encode more complicated features that we removed currently. After achieving a target error rate, we will adjust classification threshold or error metrics for sensitivity analysis. Last, we expect to apply the model on states like CA, TX, and FL where cases are the most frequent and severe, in order to answer what exactly are the causes and how to predict them.