

A Machine Learning Based Approach, For Predicting Road Closure Events, Given Data of the US Road Construction and Closure

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Abstract

A nationwide dataset of road construction and closure events, including data from 49 US states is chosen for the project. The roadwork included in this dataset's construction events ranges from minor paving repairs to significant undertakings that might take months to complete. Several APIs that provide streaming traffic incident (or event) data are used to collect the data between January 2016 and December 2021. These APIs transmit traffic information gathered by several organizations, including the US and state departments of transportation, law enforcement organizations, traffic cameras, and traffic sensors embedded in the road networks. The number of construction and shutdown records in this dataset currently stands at roughly 6.2 million.

In general, this dataset can be used for a wide range of applications, including the prediction of short- and long-term road construction, the prediction of road closures, the study of the life cycle of road construction, the development of insights to help city planners choose construction sites wisely with the most negligible negative impact on traffic flow, and the investigation of the influence of precipitation or other environmental stimuli on the need for road work. The dataset is being updated on an annual basis. The data will be obtained from US Road Construction and Closures (2016 - 2021), Kaggle, and it is available in CSV format. Presently, the dataset contains 6,170,627 observations comprising of features like Construction severity, Latitude and longitude, Precipitation, Traffic signal and many such taking a total of 47 columns. Table 1 elaborates the specifics of this data set. Using this dataset, a machine learning model will be developed to predict the duration of a new road construction project as short, medium, or long term, given inputs of pertinent features derived from Table 1. The developed model will be cross validated in four (4) folds, to be made suitable for accurate and robust predictions. With this model, it is envisaged that contractors, city planners and relevant authorities can categorize potential road construction projects based on expected average weather conditions, for better planning and project delivery.

To achieve this goal, data wrangling will be performed. The essential data frames for the study will be extracted from the original dataset followed by exploratory data analysis (EDA). EDA will enable us to derive insights by forming a pattern for better visualization and exploration. Based on this, pertinent features will be realized to build a classification model that accurately predicts the duration of a road construction project.

Table 1: Description of Undertaking Dataset

Features	Description
ID	Unique identifier of construction record
Severity	Shows the severity of the construction
Start and End Time	Shows the start time of construction
End Time	Shows the end time of construction
Latitude and Longitude	Shows the GPS coordinates
Distance	The length of the road extent affected by the construction
Street Details	Shows the street number, name and right/left side in address field
Address Details	Shows the city, county, state, country and zip code in address field
Time zone	Shows time zone based on the location of the construction event
Weather	Shows the time stamp of weather observation record

Features	Description
Temperature, Wind, Humidity, and Pressure	Shows the temperature, wind chill, humidity, and pressure
Visibility	Shows visibility
Wind Direction and Speed	Shows wind conditions
Precipitation and Weather condition	Shows precipitation and weather condition
Amenity	An annotation which indicates presence of amenity in a nearby location
Bump and Crossing	Annotations which indicate presence of speed bump or hump and crossings
Give way, Junction, railway	Annotations which indicate presence of give way, junction and railway
Exit, Roundabout, Station, Stop	Annotation which indicates presence of no exit, railway, roundabout, and station
Traffic Details	Annotations which indicate traffic calming, signal, turning loop
Light Details	Annotations which indicate sunrise, sunset, civil twilight, nautical twilight, astronomical twilight

2.0 Data Wrangling and Exploratory Data Analysis The data obtained from Kaggle is highly generic and unstructured, hence unsuited for analysis in its raw form. To achieve the goals of our design, an initial data wrangling was performed to put the data in the right format followed by EDA to determine pertinent features that affect road construction duration in USA.

2.1.1 Data Cleaning The csv file obtained from Kaggle was composed of over 6.1 million observations, which would have been computationally expensive to work with. To reduce the burden of computational time, while still retaining a good representation of the data, 1,048,575 observations (15% original data) were randomly selected with R. The data was converted to a data frame format suitable for analysis with Julia. However, some features were discovered with missing entries, which would be adversarial to subsequent codes and functions. To resolve this problem, a package in Julia (Missing package) was leveraged to filter out all observations with one or more missing entries. This process further reduced the size of the dataset to 482,849. Then, an intuitive search was made of pertinent features that could affect road construction duration, like the length of the road extent affected by the construction (denoted by "Distance" in miles), the total amount of precipitation, and other environmental factors. Although some of these pertinent features were discovered, most of the entries of each observation of these features were not in the format suitable for visualization (which requires real numbers) i.e., some variables were Strings, or Boolean values, hence the need to clean the data. Table 2 below shows a segment of the dataset after it has been roughly sampled, and missing entries removed, while Table 3 shows the summary of the dataset.

Table 2: Dataset of road construction projects in USA


 Figure 1: A square image at actual size and with a bottom caption. Loaded from the latest version of image on GitHub.

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Table 3: A summary of pertinent information of road construction projects in USA Figure ?? Image 2.png

2.2 Wrangling and feature derivation

It can be seen from Table 2 that the project duration is not explicitly stated. Hence, the project duration was defined to be the difference between the start and end time, after preprocessing the String data entries to a Date format. Table 4 shows the resulting features after preprocessing.

Table 4: Derivation of project duration from raw data Figure ?? image 3.png

Figure ?? image 4.png

Having computed the project durations as shown in Table 4, some anomalies were detected in the data. The 2nd and 3rd observations show that about 0.43mi and 0.19mi (692m and 305m) of road span was constructed in 1day respectively, whereas about 0.03mi (or 48m) was constructed in 8days as shown in the 4th entry which is unrealistic. To resolve this, a further investigation was done on the narrative of the dataset from Kaggle, and it was deduced that some of the observations were just minor repair works on existing roads (which would not take a long time irrespective of the road span) while others were new construction projects which takes longer to complete. Unfortunately, there exist no feature in the dataset that reveals if an observation was a minor repair task or a major construction task. To circumvent this, observations corresponding to project durations less than 50 days were filtered out, resulting in a dataset of 43,134 observations significantly dominated by new road construction projects or at least projects lasting longer than 50days. Furthermore, three (3) categories of projects durations were designated as short-, medium- and long-term new road construction projects. A short-term new road construction project is defined as one lasting less than 100 days, while a medium-term project lasts between 100-300 days, and a long-term project lasts longer the 300 days. Table 5 shows the resulting data after grouping into the specified classes.

Table 5: Dataset for new road construction projects in US, or projects exceeding 50days of duration

Figure ?? image 5.png

2.2.1 Feature detection and EDA

The resulting dataset as presented in Table 5, was processed to reveal key features. A rough guess was made that the numeric features quantifying environmental conditions like temperature, humidity, precipitation, wind speed, and pressure together with the road construction span or “Distance” affects the proje t duration. This can be seen from the histogram plots of these features, as there exit a considerable spread in their distributions. It was further assumed that the average amount of these quantities (e.g., Temperature) was recorded during the entire project duration, as this information was not explicitly stated in the dataset description. Thus, given the expected or average environmental conditions, and the span or extent of the road construction, the developed model is expected to predict the class of the completion time of the project as short, medium or long term. Table 6 shows the summary of the initial features selected for the development of the model.

An indispensable aspect of EDA is to detect multicollinearity and prevent confounding in the modeling. Julia’s “Statistics” package was leveraged to compute and plot the correlation between all the independent (selected features) and the dependent variable (project duration). This plot not only enabled discovery of statistically related features, but also enabled realization of features that are pertinent to predicting the dependent variable. The figures below show the correlation plots for the selected features.

The “Combinatorics” package in Julia was leveraged to create three (3) combinations of all features plus the dependent variable in order to generate the correlation plots that enabled the determination of the most relevant statistical features. A total of 56 combinations were generated and plotted in Julia, but due to space constraint, only some of the plots are presented in the figures above. The code snippet below illustrates how the figures above were generated.

It can be deduced from fig. 1 that a strong correlation exists between Temperature and Wind chill, hence Temperature was retained for the model development, while Wind chill was eliminated by choice and convenience. Following the correlation plots above, the scatter plots in figure 5, show promise in the development of classification tree networks.

Figure 5 revealed Humidity as a less promising feature for the project task because a clear cut would be difficult to achieve to develop classification trees. The following box plots in figure 6 reveal outliers in all the feature space except for Humidity. This information would guide in the selection of locations for cuts in creating decision trees. A further investigation of the statistical significance of the selected features would be done through principal component analysis (PCA). PCA will reveal the directions with most significant variance and enable the dimensional reduction of the model.

2.3 Dimensionality reduction To further explore the possibility of getting a concise representation of the dataset, and improve the model accuracy, PCA was done to transform the data and reduce the size of the feature space. This analysis revealed that with just two principal components, over 97% of the variance in the original dataset could be captured, which is a good representation of the original data and dramatically reduces the number of features to two in the PCA coordinate system. Code snippet 3 below shows the code and results obtained from the PCA analysis.

Indeed, the PCA shows promise of reducing the feature space, as scatter plots corresponding to all PCA coordinate frames shows the potential of developing a classification tree to meet the goals of this project. As with the original feature space, and outlier analysis was done to detect outliers in the PCA coordinate frames. This post process would yield better accuracy in the model development.

Although one could imagine that the first 2 principal components (that account for over 97% of the variance in the data) would be sufficient for the classification task, this is not the case. The plots in fig.7 reveal that the 4th, 5th, 6th, 7th, and 8th PCA coordinate frames also offer significant promise for the project goal. Additionally, the boxplots created for outlier detection will further guide in the decision tree creation. It can be seen from the plots in figures 7 and 8, that cuts can be made readily made to develop robust decision trees based on the Gini-impurity algorithm.

3.0. Predictive model development The predictive model development stage would leverage both the original feature space (with either Temperature or Wind chill dropped out) and the PCA feature space. Series of classification tree networks would be developed and validated with a confusion matrix plot. For the PCA-feature-space case, given a test data observation, it must be transformed to the PCA coordinate frame before evaluation on the model. As earlier stated, the model would be validated on four folds i.e., 4 sets of the original data would be created, and three would be used for training, while one (1) for testing, and this process would be repeated on all four sets of the data. This would potentially yield a robust and accurate model for the project task.

References:

1. Karimi Monsefi, Amin, Sobhan Moosavi, and Rajiv Ramnath. "Will there be a construction? Predicting road constructions based on heterogeneous spatiotemporal data.", 2022
2. US Road Construction and Closures 2016 - 2021 from Kaggle