Predictive Modeling of Effect of Weather Conditions on Road Construction Projects in USA

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Authors

- **Amirthavarshini Muraleetharan**
  677-010-487 · amirthavarshini246
  Department of CEE, University of Illinois Urbana Champaign

- **Thomas Ngare**
  652-601-317 · thomasNg
  Department of CEE, University of Illinois Urbana Champaign

- **Kapil Shah**
  668-376-620 · kapilrs2
  Department of CEE, University of Illinois Urbana Champaign

1.0 Introduction

A nationwide dataset of road construction and closure events, including data from 49 US states is chosen for the project. The projects included in this dataset's ranges from minor paving repairs to significant undertakings that might take months to complete. Several APIs that provide streaming traffic incident (or event) data were 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 is obtained from US Road Construction and Closures(2016 - 2021),from 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, making 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(short,medium or long term).

Table 1: Description of 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
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, which is 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 Exploratory Data Analysis (EDA) to determine pertinent features that affect road construction duration in USA.

2.1 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 weather parameters. 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 there was the need to clean this 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

Start_Time	End_Time	Start_Lat	Start_Lng	End_Lat	Distance(mi)	Pressure(in)	Visibility(mi)	Wind_Direction	Wind_Speed(mph)	Precipitation(in)
"4/5/2019 16:00"	"9/29/2020 11:53"	32.8384	-93.1524	32.8507	1.1035	29.72	10.0	"S"	3.0	0.0
"11/12/2021 7:59"	"11/12/2021 8:22"	30.2213	-92.0086	30.2166	0.433173	30.09	3.0	"CALM"	0.0	0.0
"10/12/2021 7:17"	"10/12/2021 9:18"	39.6532	-104.91	39.6531	0.192266	24.09	10.0	"WSW"	5.0	0.0
"2/10/2021 2:46"	"2/17/2021 23:59"	33.9615	-118.029	33.9619	0.0321121	29.92	9.0	"CALM"	0.0	0.0
"12/6/2021 7:50"	"12/6/2021 9:53"	27.8957	-82.7872	27.8946	0.141399	30.12	1.0	"SE"	5.0	0.0
"9/30/2021 1:39"	"9/30/2021 3:40"	41.977	-87.9398	41.9759	0.0732397	29.39	10.0	"CALM"	0.0	0.0
"9/16/2021 15:08"	"9/16/2021 15:40"	38.9209	-77.0365	38.9333	0.853305	30.09	10.0	"N"	20.0	0.01
"12/1/2021 8:51"	"12/1/2021 10:56"	40.8683	-73.9191	40.867	0.226995	30.15	10.0	"W"	16.0	0.0
"7/31/2021 12:11"	"7/31/2021 13:06"	33.4831	-112.074	33.4793	0.258762	28.83	10.0	"WNW"	8.0	0.0
"11/19/2021 14:06"	"11/19/2021 16:27"	33.4949	-112.028	33.4954	0.130887	28.81	10.0	"ESE"	6.0	0.0
⋮										
"7/22/2021 10:45"	"7/22/2021 11:31"	31.7066	-92.2451	31.7057	0.607945	30.04	10.0	"W"	9.0	0.0

Table 3: A summary of pertinent information of road construction projects in USA

	variable	mean	min	median	max	nmissing	eltype
1	:ID	nothing	"C-1"	nothing	"C-999999"	0	String15
2	:Severity	2.18607	1	2.0	4	0	Int64
3	:Start_Time	nothing	"1/1/2020 0:00"	nothing	"9/9/2021 9:59"	0	String31
4	:End_Time	nothing	"1/1/2017 6:00"	nothing	"9/9/2021 9:58"	0	String31
5	:Start_Lat	36.3373	24.5541	38.1765	49.0005	0	Float64
6	:Start_Lng	-91.3279	-124.531	-85.6528	-67.0758	0	Float64
7	:End_Lat	36.3376	24.5539	38.1804	49.0	0	Float64
8	:End_Lng	-91.3275	-124.518	-85.653	-67.0747	0	Float64
9	Symbol("Distance(mi)")	0.555913	0.0	0.213334	108.885	0	Float64
10	:Description	nothing	" is scheduled to be complete in Novem	nothing	"working behind barrier walls. CHARLES	0	String
⋮	more						
47	:Astronomical_Twilight	nothing	"Day"	nothing	"Night"	0	String7

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

Data before wrangling

Start_Time	End_Time	Distance(mi)
"4/5/2019 16:00"	"9/29/2020 11:53"	1.1035
"11/12/2021 7:59"	"11/12/2021 8:22"	0.433173
"10/12/2021 7:17"	"10/12/2021 9:18"	0.192266
"2/10/2021 2:46"	"2/17/2021 23:59"	0.0321121
"12/6/2021 7:50"	"12/6/2021 9:53"	0.141399
"9/30/2021 1:39"	"9/30/2021 3:40"	0.0732397
"9/16/2021 15:08"	"9/16/2021 15:40"	0.853305
"12/1/2021 8:51"	"12/1/2021 10:56"	0.226995
"7/31/2021 12:11"	"7/31/2021 13:06"	0.258762
"11/19/2021 14:06"	"11/19/2021 16:27"	0.130887
⋮		
"7/22/2021 10:45"	"7/22/2021 11:31"	0.607945

Data after wrangling

Start_Date	End_Date	Project_Duration_Days
2019-04-05	2020-09-29	544
2021-11-12	2021-11-12	1
2021-10-12	2021-10-12	1
2021-02-10	2021-02-17	8
2021-12-06	2021-12-06	1
2021-09-30	2021-09-30	1
2021-09-16	2021-09-16	1
2021-12-01	2021-12-01	1
2021-07-31	2021-07-31	1
2021-11-19	2021-11-19	1
⋮		
2021-07-22	2021-07-22	1

```
begin
    dtf = DateFormat("m-d-y")
    Start_date = Vector{Date}()
    End_date = Vector{Date}()
    for i in 1:length(df.Start_Time)
        k = findfirst(" ", df.Start_Time[i])
        k2 = findfirst(" ", df.End_Time[i])
        k = k[1]
        k2 = k2[1]
        push!(Start_date, Date(replace((df.Start_Time[i][1:k-1]), "/" => "-"),dtf))
        push!(End_date, Date(replace((df.End_Time[i][1:k2-1]),"/" => "-"),dtf))

    end
    df.Start_Date = Start_date
    df.End_Date = End_date
end
```

Julia code snippets 1

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 were constructed in 1 day, respectively, whereas about 0.03mi (or 48m) was constructed in 8 days 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 50 days. 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 50 days of duration

Start_Lng	End_Lat	End_Lng	Distance(mi)	Start_Date	End_Date	Project_Duration_Days	Project_
				Date	Date	Int64	
-93.1524	32.8507	-93.1644	1.1035	2019-04-05	2020-09-29	544	"long t
-83.2652	39.7261	-83.2465	1.10024	2020-04-20	2020-07-22	94	"short
-73.9652	40.763	-73.974	0.952071	2021-05-10	2021-12-10	215	"medium
-80.1912	26.1871	-80.1874	0.24557	2020-11-15	2021-12-30	411	"long t
-87.724	41.8312	-87.7242	0.453084	2021-07-04	2021-10-08	97	"short
-86.4798	39.6149	-86.4798	0.601812	2021-03-10	2021-12-31	297	"medium
-112.063	33.5092	-112.066	0.173348	2021-02-27	2021-12-28	305	"long t
-80.1906	25.8904	-80.1845	0.380199	2021-04-13	2021-12-13	245	"medium
-80.3374	25.7482	-80.3356	0.118257	2021-06-16	2021-12-14	182	"medium
-90.7869	42.44	-90.8007	0.701292	2021-05-14	2021-10-22	162	"medium
-92.4132	41.0376	-92.4158	0.999269	2020-07-20	2020-10-31	104	"medium

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 weather conditions like temperature, humidity, precipitation, wind speed, and pressure together with the road construction span or "Distance" affects the project duration. 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 weather 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.

Table 6: Extracted features for EDA

	Distance(mi)	Temperature(F)	Wind_Chill(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Precipitation(in)	Project_Duration_Days
1	1.1035	75.0	75.0	58	29.72	10.0	3.0	0.0	544
2	1.10024	70.0	70.0	60	28.89	10.0	5.0	0.0	94
3	0.952071	48.0	46.0	93	29.72	2.0	5.0	0.01	215
4	0.24557	72.0	72.0	78	29.88	10.0	8.0	0.0	411
5	0.453084	64.0	64.0	87	29.37	4.0	0.0	0.0	97
6	0.601812	73.0	73.0	87	29.1	7.0	6.0	0.0	297
7	0.173348	50.0	50.0	31	28.68	10.0	6.0	0.0	305
8	0.380199	71.0	71.0	84	29.95	10.0	0.0	0.0	245
9	0.118257	79.0	79.0	66	30.17	10.0	12.0	0.0	182
10	0.701292	41.0	41.0	65	29.15	10.0	3.0	0.0	162
⋮ more									
43134	0.999269	70.0	70.0	90	29.09	10.0	0.0	0.0	104

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(project duration) variable. This plot not only enabled the discovery of statistically related features, but also enabled the realization of features that are pertinent to predicting the dependent variable. The figures below show the correlation plots for the selected features.

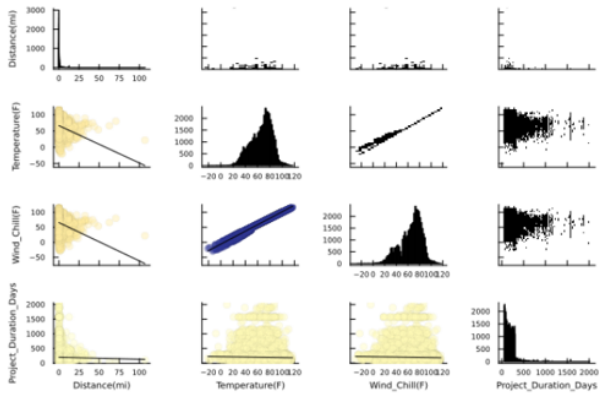


Fig. 1: Correlation plot for Distance, Temperature, Wind chill and Project Duration

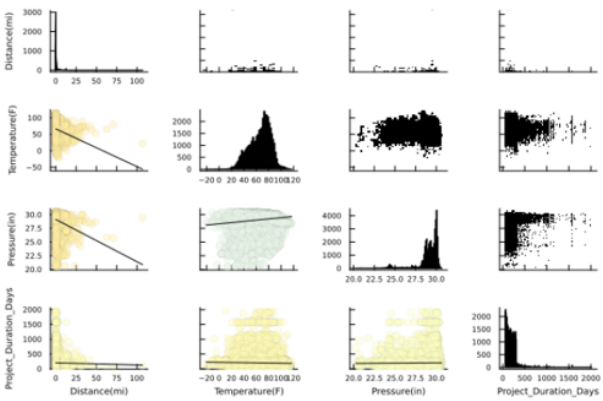


Fig. 2: Correlation plot for Distance, Temperature, Pressure and Project Duration

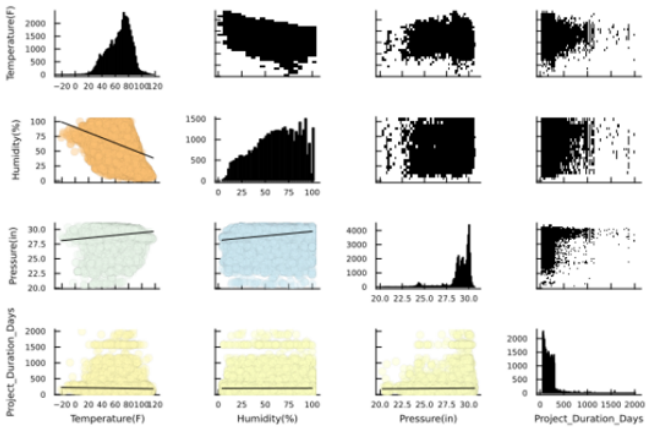


Fig. 3: Correlation plot for Temperature, Humidity, Pressure and Project Duration

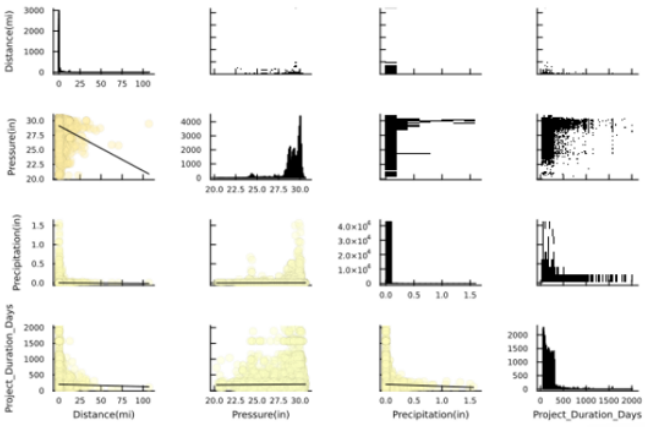


Fig. 4: Correlation plot for Distance, Pressure, Precipitation and Project Duration

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.

```
begin
    arr = collect(1:8)
    plots = []
    combinations_arr = collect(combinations(arr, 3))
    for i in combinations_arr
        push!(i, 9)
        push!(plots, @df df_sel corrplot(cols(i), grid = false, size(10000,8000),
        xtickfontsize=5, ytickfontsize=5, xguidefontsize=6, yguidefontsize=6))
    end
    plots
end
```

Julia code snippets 2

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 Fig. 5, show promise in the development of classification tree networks.

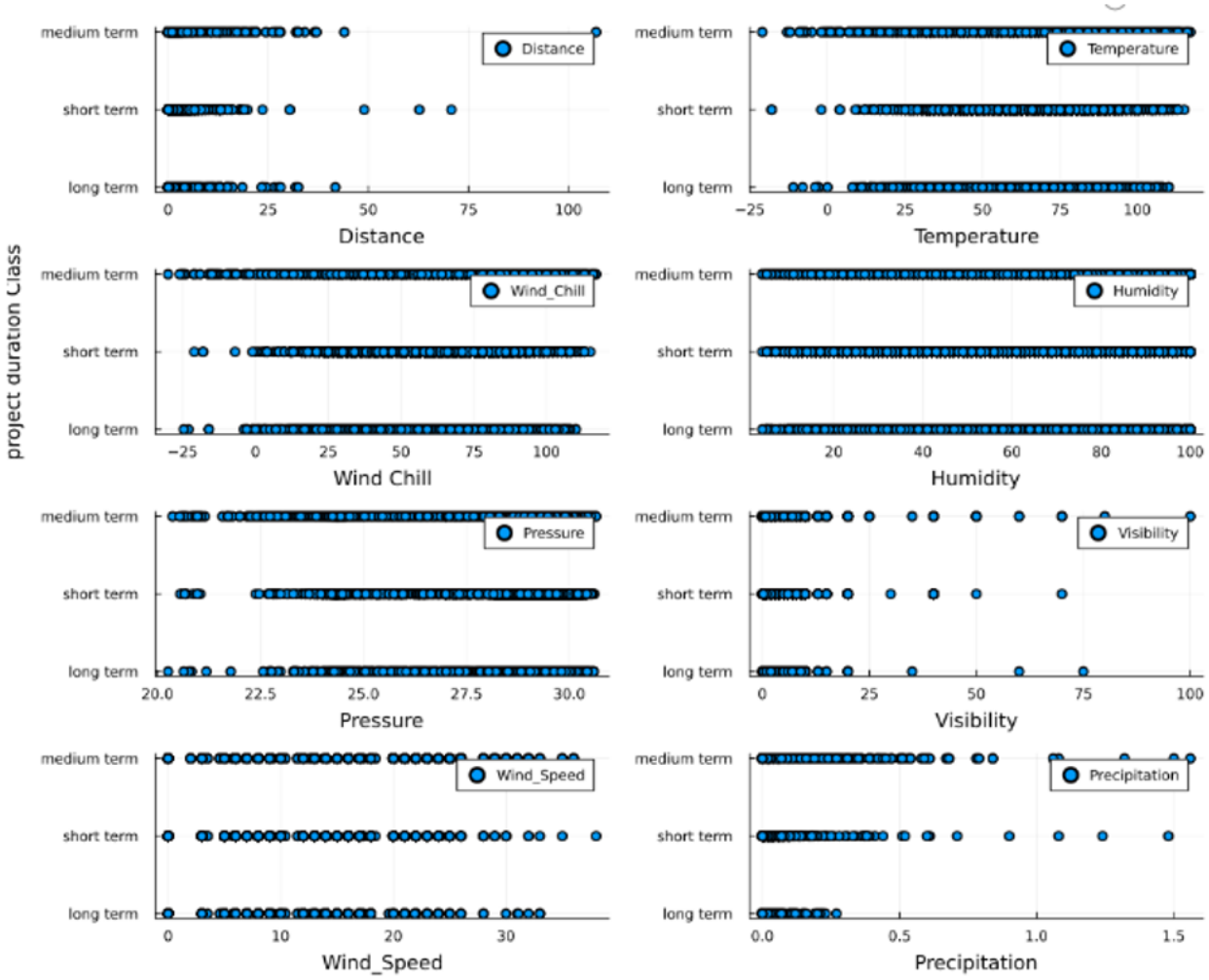


Fig. 5: Scatter plots of pertinent features against Project Duration Class

Fig. 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 Fig. 6 reveals outliers in all the feature space except for Humidity. This information would guide 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.

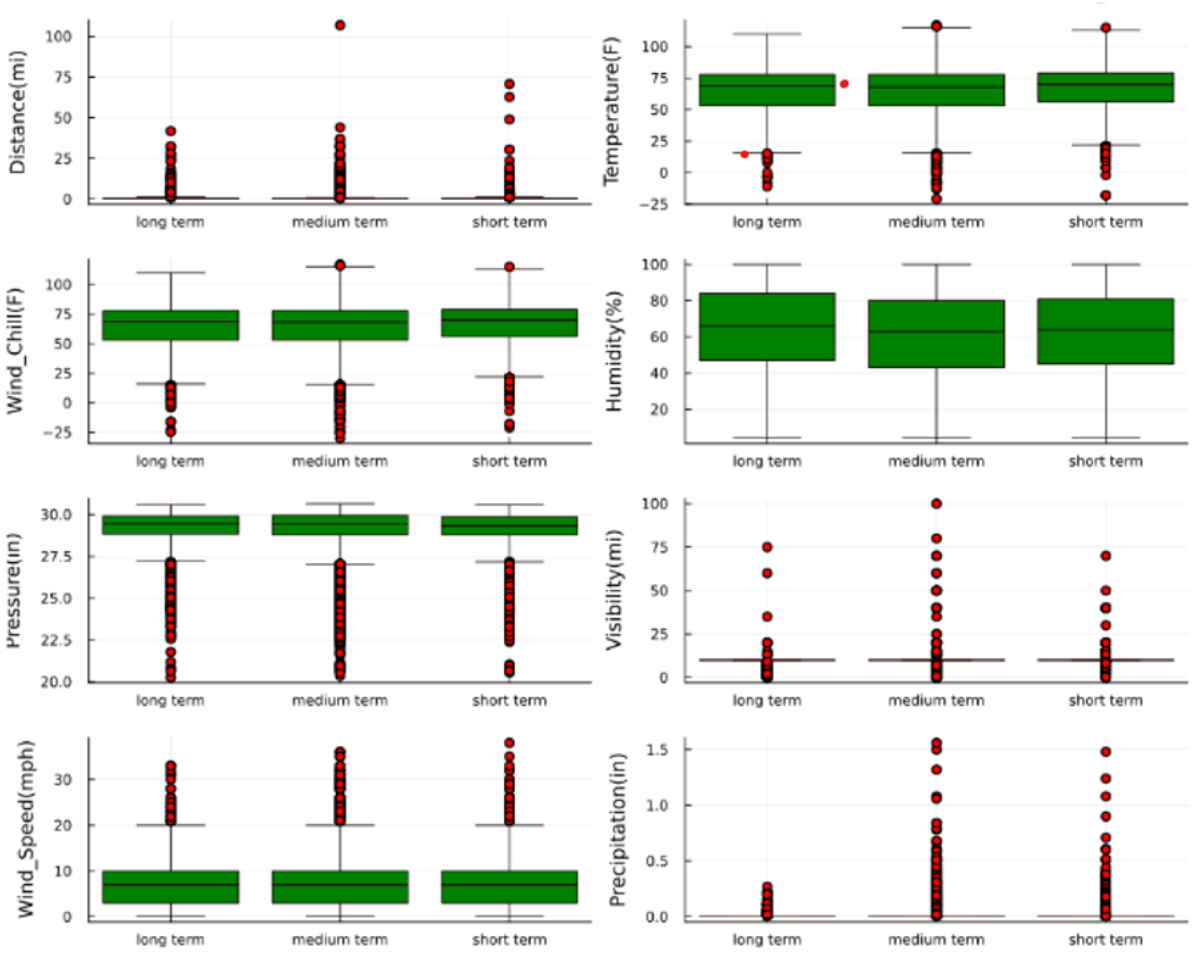


Fig. 6: Box plots for outlier detection in pertinent features

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.

Table 7: Fraction of Variance

	Number_of_Modes	Fraction_of_Variance
1	1	0.640433
2	2	0.970394
3	3	0.991476
4	4	0.995204
5	5	0.9978
6	6	0.998981
7	7	0.999999
8	8	1.0

```
begin
    var_pca = [i^2 for i in F.S]
    frac_i = []
    n_modes = []
    for i in 1:length(var_pca)
        push!(frac_i, sum(var_pca[1:i])/sum(var_pca))
        push!(n_modes, i)
    end

    PCA = DataFrame(Number_of_Modes = n_modes, Fraction_of_Variance=frac_i)

end
```

Julia code snippets 3

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.

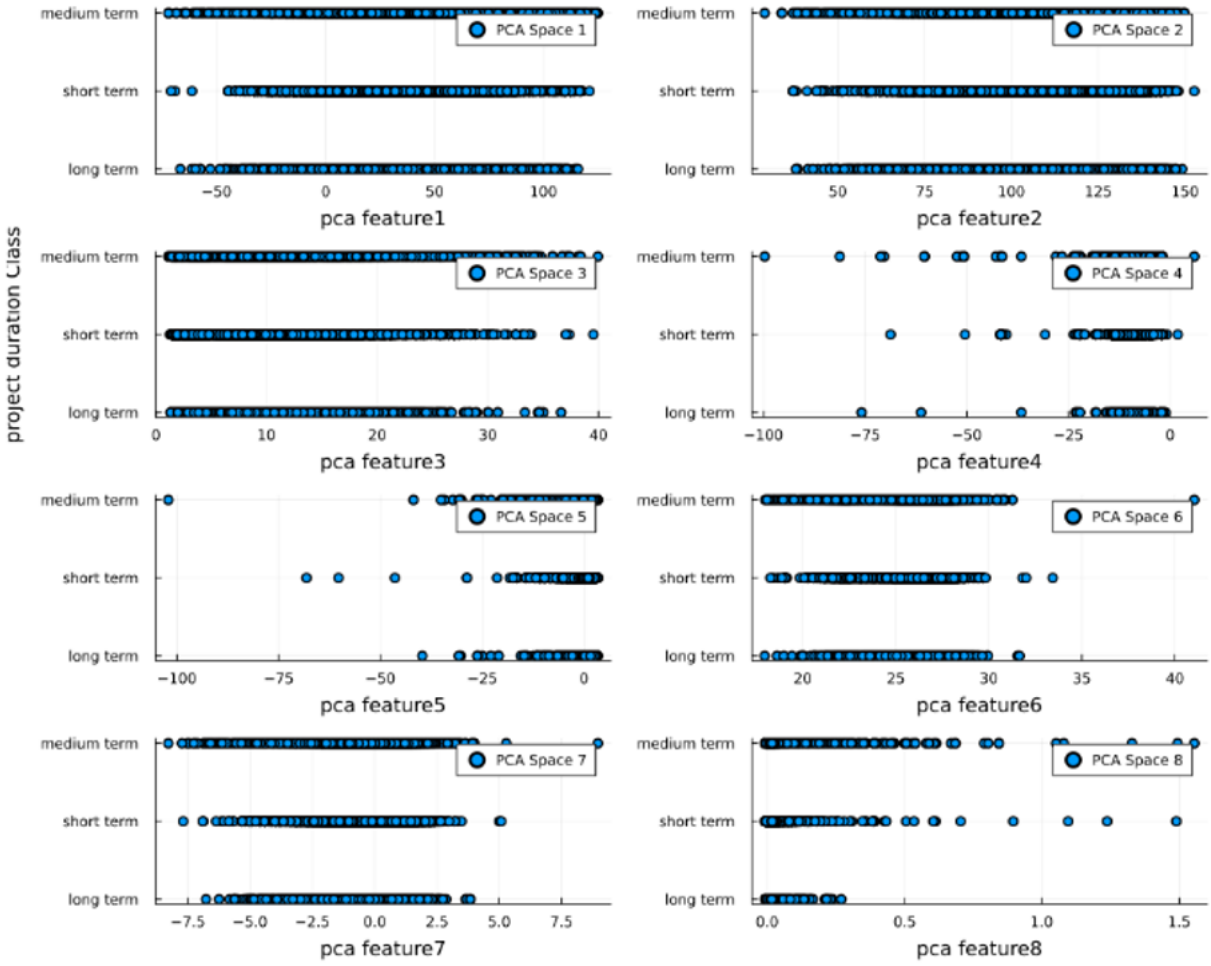


Fig. 7: Transformed data in PCA coordinate frame

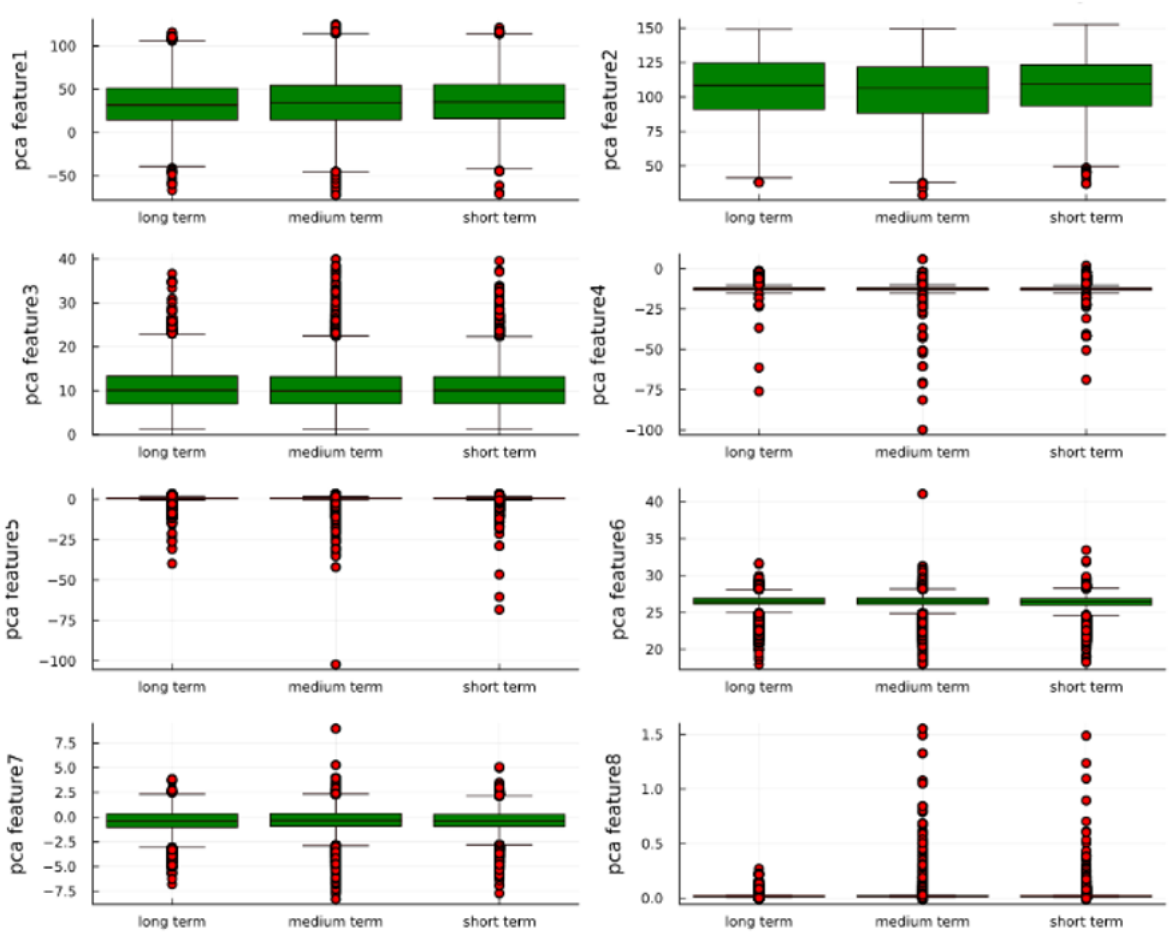


Fig. 8: Boxplots of transformed data in PCA coordinate frame

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 4^{th}, 5^{th}, 6^{th}, 7^{th}, and 8^{th} 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 Fig. 7 and 8, that cuts can be made readily made to develop robust decision trees based on the Gini-impurity algorithm.

3.0. Preliminary Modeling

3.1 Data Set for Predictive Modeling

Based on the exploratory analysis performed on the selected data set, a predictive model is built on eight potential weather features to predict the duration of road construction in terms of "short term", "medium term", or "long-term" project. This feature includes temperature, wind chill, humidity, pressure, visibility, wind speed, precipitation, and distance.

To initiate the predictive modeling, the wrangled dataset comprising pertinent features was randomly split into training set, testing set, and validation set having 60%, 20%, and 20% of observations respectively. To ensure the efficiency of predictive modeling, three kinds of datasets from the wrangled data were considered. The first dataset (case 1) was derived by defining the project duration as "short term" if the project duration is less than 100 days, "medium term" if the project duration is in between 100 through 300 days and "long term" if the project duration is greater than 300 days. The second dataset (case 2) is the PCA transformation of the first dataset's features. Lastly, the third dataset (case 3) defines a "short term" project as one with project duration less than 120 days, "medium term" if the project duration is in between 120 through 200 days and "long term" if the project duration is greater than 200 days. The third dataset innovation was explored because initial results of the first dataset were not very satisfactory, and the determination of that thresholds is quite ambiguous.

3.2 Methodology

For the model development a deep neural network (DNN) [2] architecture – the sequential model from Keras library in Tensorflow was leveraged [3]. DNN was resorted due to the high dimensionality of the feature- space and the non-existence of a physical model that relates weather conditions to road construction project duration. Hence with DNN, patterns in the data feature-space would be automatically realised, weights would be generated to fit a model to the data and predict the output (project duration labels) given inputs of weather conditions (Temperature, Pressure, etc.). This sequential model accepts a single tensor of features and observations and returns a single tensor of labels for each observation as its output. Furthermore, the Keras library offers various loss functions depending on the kind of model to be built. For this project, the categorical cross-entropy loss function [4] was leveraged for multi-class classification. Python offers great flexibility and computational speed when it comes to addressing multiclass classification problems, hence it was adopted for model development.

As inputs, Temperature, Wind chill, Humidity, Pressure, Visibility, Wind speed, Precipitation, and Distance are the features used to train the model, the input size is eight. The labels from the dataset (i.e., the dependent variable which is the project duration class) is represented in the one-hot [5] format. To get the intended predictions, three hidden layers with five neurons each were initially defined. However, the final architecture included seven hidden layers as the initial three hidden layers resulted in 65% training accuracy, which was considered suboptimal. Therefore, in addition to input, and hidden layers, parameters like learning rate – the "Adams learning rate" [3] – a regularization factor that varied from 1e-3 to 1e-6, an epoch (number of steps of

gradient descent) of 500, and a batch size of 10, were defined to complete the process of building and training the neural network. These parameters were chosen based on recommendations by [6].

Additionally, the activation function between hidden layers was set to ReLU [7], since the input data were mainly numerical data that is continuous in space. However, the sigmoid [8] activation function was used between the last hidden layer and the output, because the output is categorical i.e., "short term", "medium term" and "long term". This sigmoid function computes the probability of occurrence of each label per observation, that ranges from 0 through 1. The predicted label from various observations is the one which has maximum output probability and is assigned as 1, keeping other labels as 0. To enhance global optimality, stochastic gradient descent "sgd" [9] was also tried as the learning rate function in the model development.

3.3 Results

Having completed the model preparation and training, the open-source Sklearn [10] package was leveraged to calculate prediction metrics like precision, recall, and f-score for each class, on the test dataset and also plot confusion matrix for visualization. The confusion matrix plots and accuracy metrics after testing the models on the various test and validation datasets are presented below.

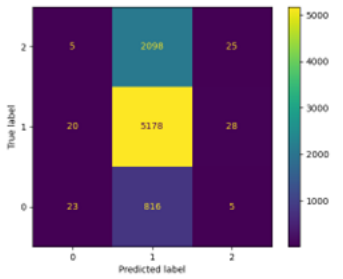


Fig 1. Confusion matrix for case 1 test dataset with 3 hidden layers of 32, 64, and 128 neurons respectively.

65% accuracy was obtained on the training data, with a loss of about 0.6. The accuracy on the training dataset was suboptimal and hence, no testing was performed on this dataset.

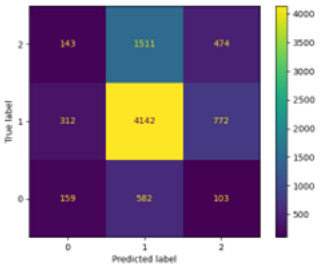


Fig 2. Confusion matrix for case 1 test dataset with 7 hidden layers of 32, 64, 128, 256, 128, 64 and 32 neurons respectively.

87% accuracy was obtained on the training data, with a loss of about 0.3

Test metrics:

Precision: 0.35, 0.66, and 0.26 for label 1, 2 and 3 respectively i.e., "short term", "medium term" and "long term"

Recall: 0.22, 0.72, 0.19, for labels 1, 2, and 3 respectively

Proportion of each class in original dataset: 25%, 65% and 0.1% for label 1, 2 and 3 respectively

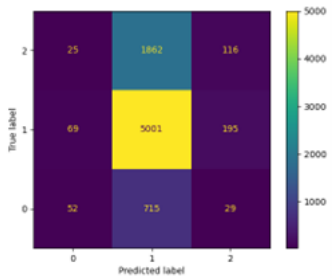


Fig 3. Confusion matrix for case 2 test dataset (i.e., case 1 dataset in PCA coordinate frame), with 7 hidden layers with 32, 64, 128, 256, 128, 64 and 32 neurons respectively.

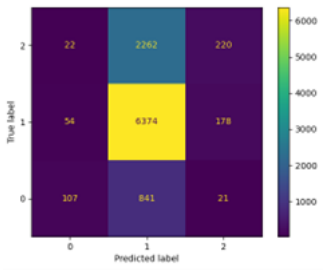
68% accuracy was obtained on the training data, with a loss of about 0.7

Test metrics:

Precision: 0.34, 0.66, and 0.36 for label 1, 2 and 3 respectively i.e., "short term", "medium term" and "long term"

Recall: 0.06, 0.95, 0.06, for labels 1, 2, and 3 respectively

Proportion of each class in original dataset: 25%, 65% and 0.1% for label 1, 2 and 3 respectively



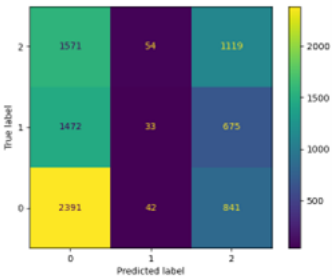
Confusion matrix for case 2 validation dataset, with 7 hidden layers with 32, 64, 128, 256, 128, 64 and 32 neurons respectively. 68% accuracy was obtained on the training data, with a loss of about 0.7

Test metrics:

Precision: 0.52, 0.67, and 0.58 for label 1, 2 and 3 respectively i.e., “short term”, “medium term” and “long term”

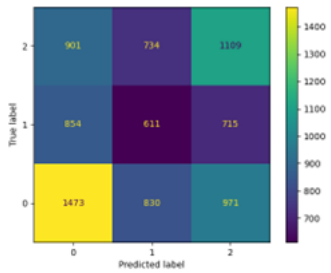
Recall: 0.08, 0.96, 0.11, for labels 1, 2, and 3 respectively

Proportion of each class in original dataset: 25%, 65% and 0.1% for label 1, 2 and 3 respectively



Confusion matrix for case 3 test dataset with 3 hidden layers of 32, 64, and 128 neurons respectively. 65% accuracy was obtained on the training data, with a loss of about 0.9

The accuracy on the training dataset was suboptimal and hence, no testing was performed on this dataset.



CConfusion matrix for case 3 test dataset with 7 hidden layers of 32, 64, 128, 256, 128, 64 and 32 neurons respectively. 78% accuracy was obtained on the training data, with a loss of about 0.5

Test metrics:

Precision: 0.41, 0.30, and 0.45 for label 1, 2 and 3 respectively i.e., “short term”, “medium term” and “long term”

Recall: 0.34, 0.29, 0.52, for labels 1, 2, and 3 respectively

Proportion of each class in original dataset: 33%, 27% and 40% for label 1, 2 and 3 respectively

3.4 Discussion and Inferences

The model development could have resulted in a better output if the data was collected keeping the projects’ objective in mind. During the data wrangling stage, some observations were unrealistic as they had a very short duration for relatively long-span projects. Despite filtering and cleaning, the assumptions evoked could not sufficiently produce the near ideal dataset intended. Even with this challenge, the developed model performs quite well in some test cases as seen in section 3.3.

It was observed that the model’s accuracy on the training data set increases with a denser neural network, and for very ambitious trials, an accuracy of about 90% was obtained on training data, even though performance on testing data was far less than 60%. This phenomenon was attributed to the possible overfitting of the training data. Therefore, such models were eschewed, and regularization enabled better generalizability of the developed models.

The developed models have also been cross validated on some portions of the original dataset. For the next steps, the authors propose to explore other techniques for improving the model to enhance generalizability. Since there is no consensus threshold that classifies project durations into the three

labels chosen in this work, the authors believe that case 3 is most realistic, since it gives an almost equal chance for classifying a given observation into the derived classes as seen from the confusion matrix plot in section 3.3. However, the difficulties currently encountered in establishing appropriate thresholds to categorize observations as “short-term,” “medium-term,” or “long-term” could present a potential research opportunity, one of figuring out which threshold produces the best/optimal classification results on cross validation. This can be seen as a problem of parameter identification or inverse analysis to determine suitable thresholds for classifying duration of road construction projects as “short term”, “medium term” or “long term”, based on which of the trail thresholds yields the best predictive model.

Finally, the key lesson learnt is that the developed model is as good as the data, therefore experiments for scientific research must be planned in a way that effectively collects data concerning the project’s stated hypothesis.

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