Model evaluation for Bridge deterioration using National Bridge Inventory Data

Introduction and background

Every four years, the American Society of Civil Engineers depicts the condition and performance of American infrastructure in the form of a school report card, assigning letter grades based on the physical condition and needed investments for improvement. Last report from 2016 scored the overall health of America's bridges as a C+, stating that one in 11 of the bridges are designated structurally deficient. [1]

Although 50 years was originally intended as the design life, bridge service life can be extended through maintenance and rehabilitation. The efficient use of public funds to keep bridges in an adequate condition requires an effective management from the federal transportation agencies. An effective tool to manage and optimize the process of inspection, maintenance and repair of bridges are Bridge Management Systems (BMS).

An essential component of a BMS is deterioration models, which are able to predict the disrepair of bridges, and can further be used to schedule and manage inspections and maintenance actions. Furthermore, the deterioration models can be used to examine the impact of certain parameters, like bridge environment or geometric characteristics, on the deterioration of bridges. In summary, bridge deterioration models contain great potential to improve decision-making processes regarding bridge maintenance.

To aid these goals, the aim of this TFM is to investigate which factors influence the deterioration of steel and concrete bridges in IECC Climate Zones 5 and 6 of the United States. For this purpose, several parameters of the National Bridge Inventory (NBI) were selected to examine whether a relationship exists between the chosen parameters and the deterioration rate of the bridge elements.

Data Source

The National Bridge Inventory (NBI) database is a unified database compiled by the Federal Highway Administration (FHWA) for all bridges and culverts in the United States that have public roads passing above or below. The database provides information on 137 characteristics of each bridge, including, but not limited to, bridge type, bridge geometric information, bridge functional description, operational condition, bridge reconstruction records and bridge inspection data. The detailed information for each item and characters can be found in the FHWA NBI coding guide.[2] The data in NBI is collected manually by the different state highway agencies and reported to the FHWA every year.

Those annual datasets can be downloaded from the FHWA website in a zip format.[3] Our reference dataset will be the one submitted on 2018, which contains 616096 bridges and culverts from the 53 states of the USA. Since our goal is to study the influence of different factors on the deterioration rate, we will also download the datasets from the 18 previous years (2000-2017).

[1] https://www.infrastructurereportcard.org/wp-content/uploads/2017/01/Bridges-Final.pdf

[2] https://www.fhwa.dot.gov/bridge/mtguide.pdf

[3] https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm

Besides, bridges in the NBI database can be geolocalized with their latitude and longitude coordinates (and previous conversion function applied on them). However, since we have focused our study on cold climate states (IECC Climate Zones 5 and 6) where snow is frequent, we believe that elevation data was also relevant. Therefore, we have used Google Maps API to access this information and combine it with the NBI data.

Data Analysis

Data Filtering

The NBI dataset is a collection of the data submitted by all the different DOTs (Department of Transportation) in the USA. Since data comes from different agencies, it presents variability in the number of fields, missing data, and how features are recorded. These discrepancies can be a challenge for data processing and cleaning when working with the NBI dataset.

In order to obtain reliable data for the deterioration rate computation, several filters have been used to eliminate incorrect and invalid data:

- Structure IDs corresponding to culverts have been dropped from the dataset
- Limit the dataset to bridges built after 1900 due to material standards (ASTM)
- Filter only bridges with steel girders and prestressed concrete decks
- Delete inconsistencies between year of construction and year of reconstruction
- Dropping duplicates and missing data
- Filter by states with IECC Climate Zones 5 and 6

Feature selection

The NBI dataset lists 137 different features for each bridge, many of which discuss location, material or characteristics of the road. Some others also include redundant or correlated information. The table below summarizes the features that we believe are related to the structural performance of a bridge. Features have been categorized into five groups: Descriptive features, Geometrical Properties, Functional Properties, Operational Conditions, and Rating Conditions. The features designated with an asterisk were not categories within the NBI, but were developed through transformation from other NBI features.

Data filtering and feature selection are developed in 01-Analysis_ALL18 notebook.

Group	Feature name	NBI #	Definition	Type of variable
Descriptive features	State code	1	Numeric (maps with State names)	Discrete
	Structure number	8	Code	Discrete
	Latitude *	16	Numeric	Continuous
	Longitude *	17	Numeric	Continuous
Geometrical properties	Traffic lanes	28A	Numeric	Continuous
	Skew angle (degrees)	34	Numeric	Continuous
	Structure kind *	43A	Steel - Concrete	Discrete
	Number of spans	45	Numeric	Continuous
	Maximum span length	48	Numeric	Continuous
	Total bridge length	49	Numeric	Continuous
	Deck width	52	Numeric	Continuous
	Surface type *	108A	Concrete - Bituminous - None	Discrete
Functional properties	Year built / Age *	27	Numeric	Continuous
	Year of reconstruction	106	Numeric	Continuous
	Design Load *	31	Heavy - Light - Other	Discrete
	Truck ADT (Avg. Daily Traffic) *	29	Numeric	Continuous

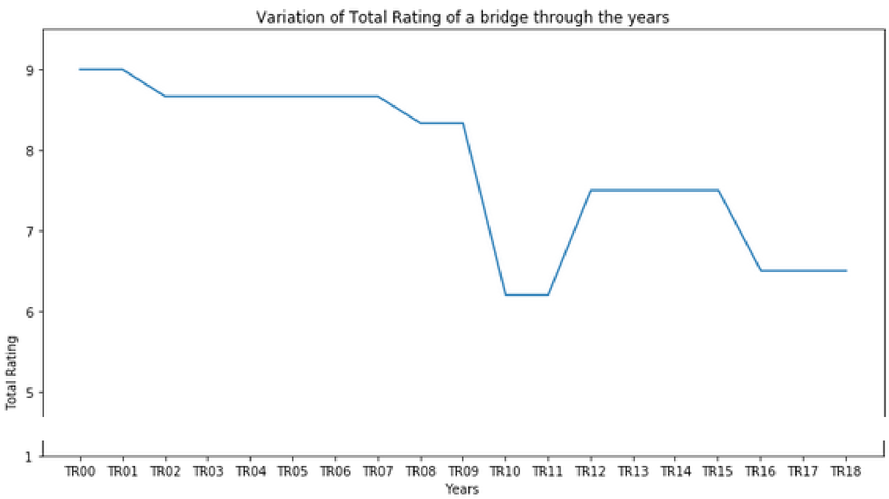
Operational cond.	Maintenance responsability *	21	State Highway Agency - Toll Agency - County HA - Town/City HA - Other A	Discrete
	Functional classification	26	Rural - Urban	Discrete
	Waterway evaluation *	71	None - Low - High	Discrete
Rating Cond.	Deck (Condition rating)	58	Ratings from 0 to 9	Discrete
	Superstructure (Condition rating)	59	Ratings from 0 to 9	Discrete
	Substructure (Condition rating)	60	Ratings from 0 to 9	Discrete

Calculation of Deterioration Rates

Items 58 through 60 of the original dataset indicate the condition ratings of every bridge. Those ratings are used to describe the existing bridge as compared to the as-built condition. Evaluation is performed for the physical condition of the deck, superstructure, and substructure components of the bridge. In order to unify those ratings, a new feature called "Total Rating" will be created.

$$TR = \begin{cases} \min(DR, SBR, SPR), & if \min(DR, SBR, SPR) \leq 4 \\ \dfrac{DR + SBR + SPR}{3}, & if \min(DR, SBR, SPR) \geq 8 \\ 0.5 * min\_val + 0.2 * \max\_val + 0.3 * remaining\_val & \end{cases}$$

Total Rating will be calculated for every bridge in the whole set of 19 years records we have downloaded. Therefore, a figure similar to the one shown below will be obtained for every bridge.



The deterioration rate defined in this study indicates the average change of condition rating over a one-year period. The bridge shown above has a decreasing rating behavior, except between years 2011 and 2012, where the bridge experienced an improvement which leads to an increase in the total rating from 6.3 to 7.5. Such improvements are most likely the results of applied maintenance actions, but could also be a result of inspector subjectivity. However, since the aim of this study is to investigate natural working bridge deterioration, transitions to an increased condition rating were not considered in the computation of the deterioration rates.

Therefore, the deterioration rate is calculated by dividing the total rating evolution into several time periods, which are characterized by no increase in rating. For each time period, a deterioration rate was calculated, which is the total difference in rating divided by the difference in years of that time period. The final deterioration rate is computed by calculating the average of all deterioration rates of each time period. For instance, applying this approach to the example above, two time periods can be used. For the first time period, from 2000 to 2011, the deterioration rate would be calculated as (9−6.3)/(2011-2000) = 0.245, and for the second period, the deterioration rate would be (7.5−6.6)/(2018-2012) = 0.15. Then, the final deterioration rate would then be calculated as (0.245+0.15)/2=0.198, which means that the bridge decreases its condition rating, and hence deteriorate, by 19.8% within one year.

Deterioration rate calculations are developed in 02-Data_Merge_CLIM notebook.

Merging elevations from Google Maps API

In cold climate regions, snow is frequent and de-icing techniques are used on roadways to prevent accidents. The use of road salts and chemicals is cost effective but causes damage to concrete and corrosion of reinforcing steel. We have decided to introduce this environmental factor in the dataset by including the elevation of each bridge. We have used Google Maps API, that returns elevations when providing latitude and longitude coordinates.

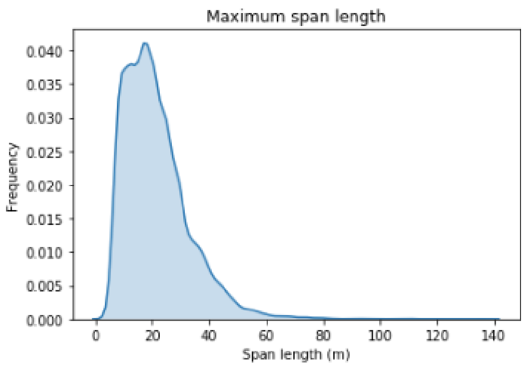
Elevation requests are developed in 0x-Import_CLIM_elev notebook, that will be submitted separately since it contains sensitive information.

Exploratory Data Analysis

Several visualization techniques have been used to plot the distribution of individual variables present in the dataset and their relationship with other features. This visual inspection has allowed us to check for outliers and inconsistent data we missed on previous steps of our analysis.

The information we can read from those plots endorse basic civil engineering concepts for beam bridges that can be found in several technical books and that come from the expertise of many years of investigation of structures evolution. Two main concepts we have been able to corroborate during this analysis have been:

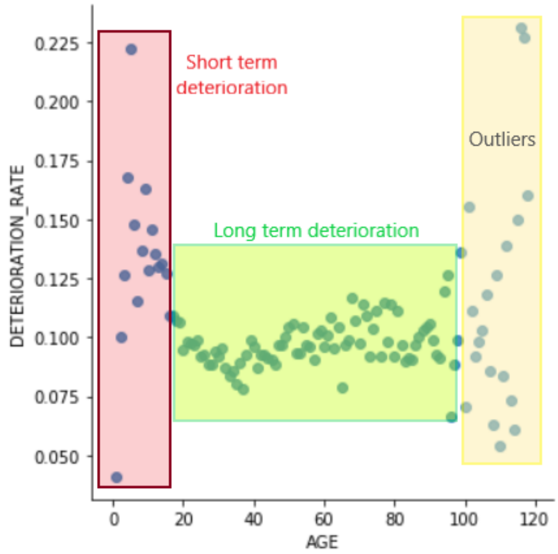
- Typical girder bridges span length varies from 15 to 40 m as states the Spanish Transportation Ministry recommendations for bridges with girder decks.



- Deterioration on structures has two separated paces:
    - Short-term deterioration rates are above the mean and correspond to different effects of the structure evolution (such as shrinkage or corrosion of structural steel) that appear since the first years of bridge service life. Those deteriorations (cracks, presence of rust…) have to be reported by the inspection engineer but do not usually affect the bridge integrity. In fact, they cannot be counteracted, they just prove that the bridge is not a deadless structure.

    - Long-term deterioration rates follow a more constant path. After those initial moments in the bridge lifetime, where the structure has been through all this transformations, the structure's inner forces have been compensated and the difference between consecutive years ratings shouldn't vary so sharply if the bridge is in good health. However, other deterioration phenomena that are not intrinsic to the structure's behavior can affect the bridge. Those are the effects we want to predict in our analysis.

Therefore, we have limited the age of the bridges we are going to consider in our analysis in order to focus on the long-term deterioration rates and what features have an influence on them.

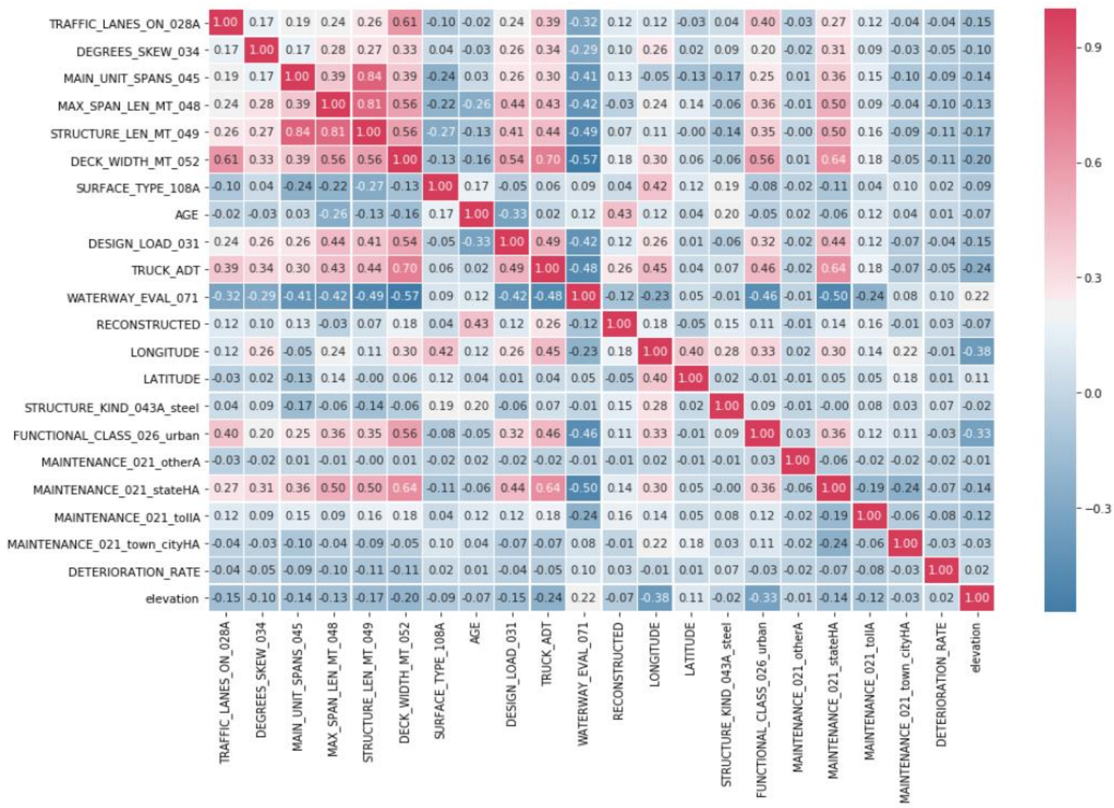


Visualizations and corresponding interpretations are developed in 03-EDA_CLIM notebook.

Machine Learning

Correlation and Feature selection

Features that are highly correlated can cause over-fitting in the model. We will check the correlation between features to remove some of them, and correlation between features and the dependent variable.



Deck width and structure length have the highest correlation to the deterioration rate, but with a value of 0.11, they are only weakly correlated.

Feature scaling

The dataset contains features highly varying in magnitudes. We will need to implement some scaling to those features so that a particular variable doesn't dominate others in the dataset. Besides, some of our independent features come from labeled data and others from continuous variables.

We have applied normalization (MinMaxScaler()) to the independent features so that continuous values vary between 0 and 1. Then, for our target feature, we have decided not to apply any scaling factor since values are already between 0 and 1.

Model selection

We will use regression models to predict the deterioration rate of bridges. Since our data has already been transformed, next step in this modelling process is to fit the data to a model. We have separated the dataset into train and test data (85% and 15% respectively). We will start working with the following models:

- Mean model: the simplest model we can get, where the predictions of all the values are equal to the average of the train set we have established.
- Linear regression model: we will fit the train data and predict with the test data
- Ridge regression model: we will fit the train data to this model using a GridSearch over alpha hyperparameter.

The metrics we will use to check the performance of our models are MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) since our goal is to minimize the difference between the prediction and the actual value and to penalize bigger errors. We will also check R2 score to see the goodness of fit of the independent variables.

Ridge regression performs quite like the simple linear regression model. It seems that our data might not be well suited for linear models.

We will start applying more complex models to try to take into account the non-linearity of the data and improve performance. Gradient Boosting and Random Forest models will be applied with GridSearch for hyperparameter tunning and cross-validation to avoid overfitting.

The metrics of the different models are shown below:

Metric	Mean model	Linear regression	Ridge regression	Gradient Boosting	Random Forest
MAE	0.0519841	0.050852	0.050837	0.046076	0.046351
RMSE	0.0692285	0.068132	0.068131	0.063759	0.063581
R2_score	-	0.031417	0.031457	0.151760	0.156483

Ensemble models outperform linear regressions both in reducing the prediction error and in explaining the target variable through the remaining features of our dataset.

Model selection process is developed in 04-Model_CLIM notebook.

Conclusions

Following are the main conclusions of this study:

- If we check the rank of features importance in those two last models, we can see that a few explanatory variables were found to influence the prediction accuracy. In fact, the geographical coordinates (longitude and latitude) are both important for deterioration rate predictions. Geometrical bridge data such as deck width and structure length together with the age of the bridge also have some influence on the deterioration rate. However, none of the functional and operational characteristics of the bridge seems to be decisive for the analysis.

	Feature	Importance
0	LONGITUDE	0.281908
1	LATITUDE	0.134534
2	DECK_WIDTH_MT_052	0.113090
3	STRUCTURE_LEN_MT_049	0.095265
4	AGE	0.083091
5	elevation	0.079835

- The best value we have obtained for RMSE is the one given by the Random Forest model, which is 0.06358. Since we have not performed any scaling on the deterioration rate feature, we can directly read into it. An error of 0.06358 in deterioration rate means that we would be underrating 6% of the deterioration of a bridge per year.

- The Random Forest model only has 16% of variance explained by the independent variables. The values we have obtained for R2 scores are less than what we would have expected at the beginning of this analysis. This is because other variances that could cause the bridge deterioration are not available or have been excluded from the dataset. From our side, the initial feature selection from the 137 columns of the NBI dataset was made following the recommendations of qualified structural engineers with proven experience on bridge inspection and rehabilitation. Other features like the amount of maintenance funds applied to each bridge, more climatic variables such as sea proximity, environmental humidity and amount of precipitation, or suitability of construction conditions like concrete curing time or distinction between in-situ and precast elements might also be decisive for deterioration rate prediction but were not available for this study.