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Project Title

Descriptive and Predictive Deep Learning Analytical Tools for Enhanced Bridge Management: Bridge Subtyping and Bridge Deterioration Forecasting

University

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Research Needs

Bridges deteriorate with time and use. The deterioration process is affected by several factors, such as structural materials, structural design and behavior, daily traffic, freeze and thaw cycles, climate, pollution, temperature variation[1, 2, 3]. After a certain period of time has elapsed, the deterioration processes accelerate and in a relatively short time interval the components can lose the capacity to carry the loads they were designed to support.

To address this national issue, several US Acts[4] mandate the state and local governmental agencies (including cities, state transportation agencies, etc.) to perform regular bridge inspections. These Acts define the requirements, periodicity, and procedures for such inspections in the US. Inspections are required to assess the extension, implications, and current state of deterioration processes that may exist, and they need to be performed at regular time intervals not longer than 2 years. A bridge report is generated after each inspection. All bridge reports collect and offer specific data about health of the inspected bridge, including sufficiency rating, condition rating, structure identification, year built, average daily traffic, and average daily truck traffic. For example, condition ratings (aka condition indexes) are quantitative descriptors of the state of structure parts that can be used in the assessment for the structures maintenance[3, 4]. By associating a deteriorated state to a number, instead of using qualitative description of the state, much more flexibility can be achieved in monitoring groups of similar structures[5-10]. The adoption of condition ratings in the evaluation of structures allows consistency and uniformity, making it possible to compare structural performance, establish priorities, and also prevent failures and accidents.

The aforementioned inspections across the nation, which have been conducted since 1970's (including our region), have generated valuable historic databases of bridge data based in local and state governmental agencies. While these agencies currently use these inspections to prevent failure and to administrate the national bridge network by setting priorities and establishing criteria to allocate available resources to the structures in most critical conditions, we believe these databases are heavily underutilized. In particular, with the advent of machine learning and data mining methods, we envision data-driven solutions that can derive much more valued hidden knowledge that can be utilized for enhanced bridge management.

While in the past, various data-driven deterioration models including Bayesian models, probit model, and Markov chains are proposed in the literature to model bridge deterioration [2, 3, 11-15], these models either suffer from low accuracy or are too complex to be applicable. Moreover, they only address the problem of deterioration forecasting. Recently deep learning is shown to significantly outperform other analytical modeling methodologies in a variety of application domains, such as computational biology, Electronic Health Record (EHR) data analysis, activity detection, scene labeling, image captioning, and object detection[16-24]. In the past, we have introduced and deployed various deep learning based models, e.g., for sleep stages classification using brain signals[25-26], mobility monitoring [27-28], and activity classification[29]. In this study, we propose to develop deep learning models for enhanced bridge management. In particular we focus on the two problems of *bridge subtyping* (descriptive analysis) and *bridge deterioration forecasting* (predictive analysis). In addition, we will leverage the proposed models for bridge deterioration and bridge subtyping to introduce a method for *anomaly detection*. Effective solutions for these problems will significantly enhance the state-of-the-art in bridge management as we elaborate in the following section.

Research Objectives

In this project, we propose to leverage the historic bridge data and develop the following tools for enhanced bridge management:

1. <u>Bridge Subtyping Tool for Descriptive Analysis</u>: With this tool one can perform descriptive analysis of the bridges and their performance by (1) objectively categorizing bridges based on their quality and deterioration performance given static and dynamic features associated with each bridge per bridge inspection reports, (2) analyzing and determining the hidden links between bridge performance and bridge structural properties, utilization statistics, and environmental characteristics in each category, and finally (3) identifying the distinct features as well as characteristic behavioral and performance trends for bridges in each category. In turn, this knowledge can be effectively used not only to make more informed choices in maintenance and repair planning for existing bridges, but also to make better design choices in building new bridges. Figure 1 illustrates our preliminary results from a pilot study to demonstrate feasibility of bridge subtyping given a test bridge dataset. As shown in the figure, four very distinct categories/clusters of bridges (corresponding to the 4 light colored

squares in the figure) have emerged in this dataset. With this project, we plan to extend our pilot study by introducing advanced methods for enhanced bridge clustering and subtyping as explained above.

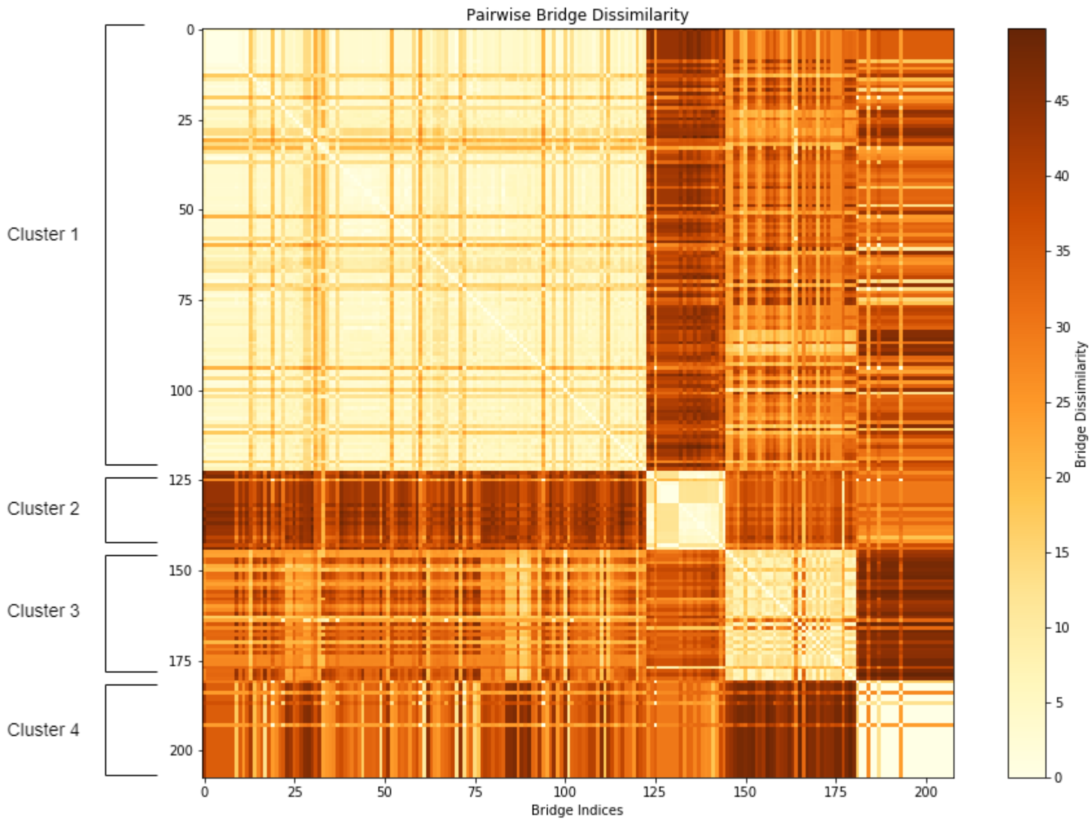

Fig. 1 *Bridge clusters identified in the City and County of Denver Bridge Dataset (1986-2014)*

2. <u>Bridge Deterioration Forecasting Tool for Predictive Analysis</u>: With this tool one can perform predictive analysis of the bridges by accurate prediction of quantitative descriptors for the structure deterioration state (e.g., condition ratings) as well as any possible anomalies in the deterioration pattern of the bridge structure. Accurate prediction of these descriptors and anomalies are not only crucial in establishing maintenance priorities and performing proactive bridge monitoring with optimized resource allocation, but also more importantly essential for failure prevention. Figure 2 depicts the deterioration curves of a number of bridges in City and County of Denver (CCD) based on the reported inspection data in a test dataset. This figure shows variety of deterioration trends, and demonstrates the need for accurate data-driven models that can predict deterioration patterns and potential anomalies for each individual bridge with sufficient precision.

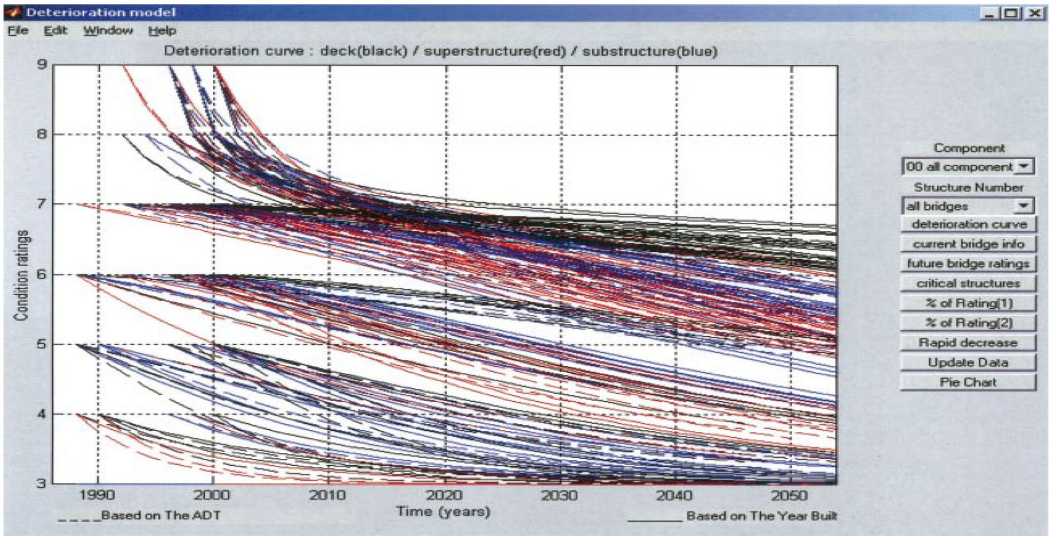

Fig. 2 *Bridge deterioration patterns for a number of bridges in the City and County of Denver*

3. <u>Accurate and Early Detection of Bridge Performance Anomalies</u>: Bridge failures are frequent accidents that are often costly to address, and at times claim considerable number of human lives[1]. With this project, our main goal is to build on our prior work in successfully developing deep learning models for accurate bridge deterioration forecasting and bridge subtyping, and introduce deep learning based anomaly detection methods for early detection of anomalous bridge performance (e.g., anomalous condition rating curves). Accurate prediction of such anomalies is not only crucial in establishing maintenance priorities and performing proactive bridge monitoring with optimized resource allocation, but also more importantly essential for failure prevention.

To conclude, our proposed automated tools allow for enhanced bridge management by improving depth, accuracy, and efficiency/speed in descriptive and predictive analysis of the historic bridge data reported by bridge inspectors. In turn, this can lead into more effective resource allocation for bridge monitoring, maintenance, and construction. For instance, in a hypothetical situation, if complete failure (and the reconstruction) of a bridge can be prevented by early and low-cost repair given deep, accurate and frequent/real-time assessment enabled by our proposed tools, considering a 10,000 sf bridge built at an average cost of $250.00 per sf, savings of close to $2.5 M can be achieved.

[1] See the long and growing list of bridge failures here: https://en.wikipedia.org/wiki/List_of_bridge_failures

We summarize the objectives of our project as follows:

1. Design deep learning based tools for bridge subtyping, bridge deterioration forecasting, and bridge anomaly detection;
2. Develop the designed deep learning based tools for bridge subtyping, bridge deterioration forecasting, and bridge anomaly detection;
3. Evaluate the developed tools versus existing solutions (where available) using a real historic bridge dataset from CCD, covering all CCD inspection reports generated from 1986 to 2014;
4. Advance policy and practice with respect to bridge management by presenting the developed tools to local and state governmental agencies (including CCD and CDOT);
5. Advance education through training students on the topic and results of our project; and
6. Advance knowledge and build an evidence base by disseminating findings through publications and presentations.

Research Methods

Below, we will review our proposed methodology toward achieving the aforementioned objectives, where applicable:

<u>Deep Learning Methods for Design of Proposed Tools</u>: As mentioned above, in the past we have introduced various deep learning models deployed in real-world scenarios within other application domains, e.g., for sleep stages classification, mobility monitoring, and activity classification. With this proposal, as we explain below we will build on and significantly extend the solutions we proposed in two of our prior work focused on subtyping (aka clustering) [27] and prediction (aka classification) [29] to develop the deep learning models that enable our bridge subtyping and bridge deterioration forecasting tools, respectively.

In our prior study [27], we introduced a subtyping pipeline that begins with a Convolutional-Recurrent Autoencoder (see Figure 3), which performs featurization and dimensionality reduction to transform each input time series into a low-dimensional fixed-length feature vector. These feature vectors are then fed as input to a clustering algorithm, including K-Means, DBSCAN, and MineClus [31] to partition the data into groups of inputs with similar variation patterns. The convolutional layers extract features along the time domain, reducing the time series to a sequence of temporal features. The set of temporal features is then fed into the LSTM Encoder/Decoder. The Encoder encodes the temporal features into a fixed-dimensional feature vector. The Decoder is then trained to reconstruct this sequence of features, using only the feature vector as input. Once trained, the final state output of the Encoder LSTM contains a fixed-length vector which represents of the time series allows for efficient clustering.

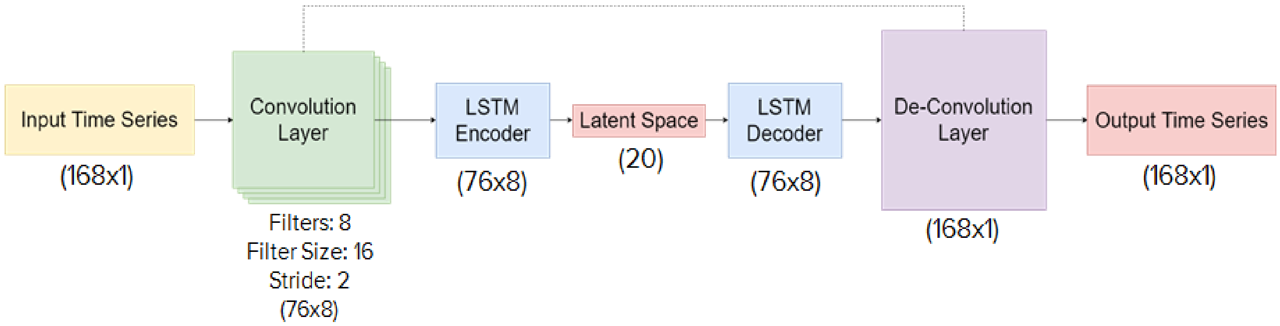

***Fig. 3** Template subtyping deep learning model to be adopted and adapted from prior work* [27]

We plan to adopt and adapt this model to develop our deep learning model for bridge subtyping. While this base model captures the general structure of the desirable model for bridge subtyping, given the major differences in data type, size and semantics between bridge subtyping and the application studied in [27], we anticipate major extensions are required for adaptation of the adopted model before it is customized for bridge subtyping.

Similarly, in study [29] we developed a multi-layer convolutional neural network (CNN) for accurate prediction/classification of an outcome in a medical application. To design the deep learning model for bridge deterioration forecasting, we will develop a variation of this multi-layer CNN model which implements classification by composition of sparse convolutional layers and local pooling steps that match with the local properties of the bridge structures. As a result, such as network can effectively capture the properties of the bridge components that can serve as strong predictors for bridge deterioration forecasting. In addition given that such networks require a large training set, to ensure we have sufficient samples in our test data (see below) to reliably train our models for high distinctive power and generalizability, inspired by Denoising Autoencoder (DAE) [30] we use a sample-expansion technique that introduces perturbed features to extend the sample set.

Finally, one of the most successful anomaly detection approaches is outlier detection based on clustering. The main idea behind using clustering for anomaly/outlier detection is to learn the normal mode(s) in the data already available (train) and then using this information to point out if one point is anomalous or not when new data is provided (test). In particular, in our case the data points are time series data that capture the bridge performance (such as condition ratings for deck, superstructure, substructure) for each bridge. Therefore, the main component of our proposed methods are time series clustering techniques that can effectively identify bridge clusters/groups based on their temporal performance readings.

Our proposed clustering framework is a semi-supervised CAE model, which combines an unsupervised reconstruction loss (L_{rc}) with a semisupervised loss L_{sup}, as shown in Figure 4. We will adopt and adapt existing semi-supervised learning objective functions based on Silhouette Loss to fit into our model. We focus on optimizing the autoencoder's latent space for distance-based clustering algorithms such as K-Means. The spherical, centroid-based clusters generated by k-Means are a good fit for the proposed semi-supervised losses, which encourage each cluster to converge around a single high-density point.

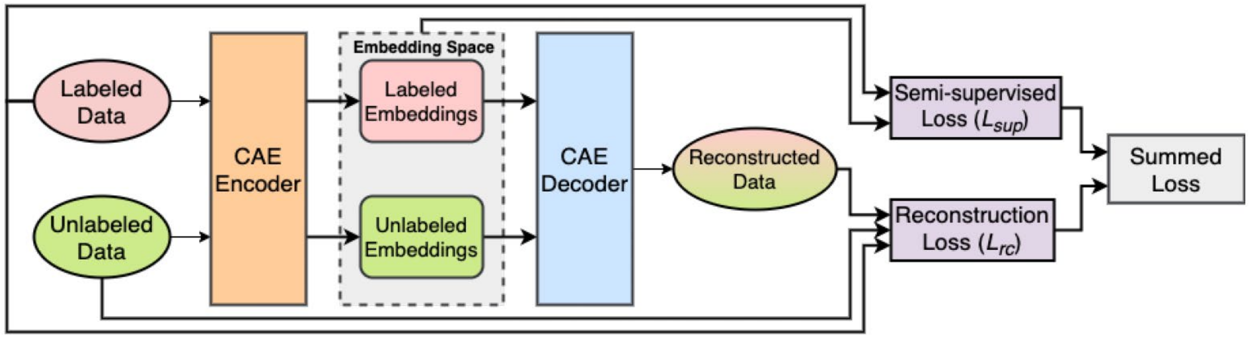

***Fig.** 4 Outline of the Proposed Time Series Clustering for Bridge Performance Anomaly Detection*

Software for Development of Proposed Tools: We will develop the aforementioned deep learning models for bridge subtyping and bridge deterioration forecasting mainly using the open access TensorFlow deep network modeling platform from Google. TensorFlow is installed and available for use at PI's research laboratory, Big Data Mining and Management Lab (BDLab), which is also equipped with a high efficiency cluster computing systems with GPU nodes.

Test Data for Evaluation of Proposed Tools: We have access to the historic database that contains all bridge inspection reports performed for all bridges in jurisdiction of City and County of Denver (CCD) between 1986 and 2014. The number of CCD bridges covered in the dataset is 208, each with at least 15 inspection reports, where each report offers 432 data points (116 unique data types) for static and dynamic features, most notably sufficiency rating (field 137), condition ratings (fields 58, 59, and 60), structure identification (field 8), year built (field 27), average daily traffic (field 29), and average daily truck traffic (field 109)[2]. Although we believe the CCD dataset serves our purpose for design and evaluation of the proposed tools, we have also started communicating with Colorado Department of Transportation (CDOT) to obtain formal approval for access to the corresponding CDOT bridge inspection dataset. If we received access to the CDOT dataset we will include a replication study during evaluation of the proposed tools (Objective #3 above).

Dissemination: Dissemination of results from this project will target both academic and practitioner audiences. To reach academic audiences, we will produce conference presentations and peer-reviewed conference and journal papers to share findings of this project. Yet, even the best transportation research is of little value until that knowledge is effectively shared with a broader audience. Accordingly, we will make sure that the results are adapted for practitioner audiences, particularly via popular press articles. Specifically, to encourage technology transfer, we will present a research seminar via the Transportation Learning Network.

[2] The data catalog for this dataset is available upon reviewers' request.

Expected Outcomes

The expected outcomes of this work include:

1. Three novel deep learning models and the corresponding tools for automated data-driven bridge subtyping, bridge deterioration forecasting and bridge anomaly detection; these models will also likely inspire more research in this area that can generate other deep learning based tools for enhanced data-driven bridge management;
2. Education materials on the topic of data-driven bridge management with a focus on deep-learning based solutions;
3. Presentations to academic, practice, and policy audiences;
4. Manuscripts for presentation/publication at TRB and other peer-reviewed journals reporting results of the project; and finally
5. Periodic reports and final report of the project progress and results for MPC.

In addition, our proposed data-driven bridge management tools can possibly be implemented as applications and offered to governmental agencies for their daily use, potentially resulting in significant improvement in bridge management at the regional and national levels.

Relevance to Strategic Goals

By improving resource allocation and capabilities for bridge maintenance and repair, the proposed research is well aligned with the following USDOT strategic goal: State of Good Repair (to ensure the U.S. proactively maintains critical transportation infrastructure in a state of good repair). A secondary USDOT strategic goal also addressed by this research project is Economic Competitiveness (to promote transportation policies and investments that bring lasting and equitable economic benefits to the Nation and its citizens); toward this end the proposed tools can be used to evaluate bridge design choices based on the historic bridge inspection databases, and accordingly inform investments in building new bridges for higher cost-efficiency.

Educational Benefits

The students involved in this project (one PhD student and one MS student) will be trained in conducting research related to the field of transportation, in particular bridge management. These students will gain valuable research experience and have the opportunity to author publications and presentations emanating from this work.

The results of this study will be integrated into Drs. Banaei-Kashani's and Nogueira's graduate courses as case studies that will be presented to the students and also incorporated into their term projects. The data collected for this project will also be made available to students for use in term projects and/or master's/PhD reports. As a result, this project will influence students from a variety of disciplines (in particular, transportation and data science) that comprise our future transportation professionals.

Technology Transfer

As mentioned before, the results of this study will be presented in relevant courses offered by the PI and Co-PI, and disseminated through research publications and presentations. Moreover, we will present seminars in transportation practitioners' groups, such as the Transportation Learning

Network, to communicate our results to practitioners in addition to researchers. Finally, the PI and Co-PI will also leverage their existing partnerships with relevant federal and state agencies (namely, CDOT, NREL, and CCD) to explore technology transfer and policy impact opportunities based on the results of this study. For example, for years the City and County of Denver has partnered with the Department of Civil Engineering, University of Colorado Denver (i.e., the home department of the Co-PI Nogueira) to perform nearly all bridge inspections across CCD. We will leverage this and other existing partnerships to actively engage potential adopters of our proposed bridge management tools for technology transfer.

Work Plan

The proposed scope of work is scheduled for a one-year timeframe, beginning with notice to proceed from the Mountain-Plains Consortium. Major project objectives and milestones were described in previous sections. Here, we list the corresponding tasks and present the timeline to implement these tasks:

Task	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Designing Deep Learning Models for Data-Driven **Bridge Subtyping**												
Designing Deep Learning Models for Data-Driven **Bridge Deterioration Forecasting** and **Anomaly Detection**												
Developing **Bridge Subtyping** Tool based on Designed Deep Learning Model												
Developing **Bridge Deterioration Forecasting** and **Anomaly Detection** Tool based on Designed Deep Learning Model												
Executing Comparative Evaluation to Assess Performance of **Bridge Subtyping** Tool												
Executing Comparative Evaluation to Assess Performance of **Bridge Deterioration Forecasting** Tool and **Anomaly Detection** Tool												

Incorporating Lessons into Graduate Courses												
Advancing Policy, Practice and Research by Dissemination / Technology Transfer												

Project Cost

Total Project Cost	$160,000
MPC Funds Requested	$ 80,000
Matching Funds	$ 80,000
Source of Matching Funds:	University of Colorado Denver

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