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Project Title

Improving Deep Learning Models for Bridge Management Using Physics-Based Deep Learning

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 (DL) 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]. With our previous MPC project, building on our extensive experience in deploying DL in a variety of applications[25-29], we have developed DL models for enhanced bridge management. In particular, we focused on the two problems of *bridge subtyping* (descriptive analysis) and *bridge deterioration forecasting* (predictive analysis). Our preliminary results show that DL based models for bridge subtyping and bridge deterioration can be used to effectively enhance bridge management.

While our existing DL models are effective in bridge management, *they solely rely on data, and unlike physics-based bridge models, cannot benefit from the vast knowledge and experience of bridge engineers encoded in existing physics-based models*. As a result, accuracy and efficiency of these models are suboptimal. With this proposal, we intend to develop *hybrid physics-based DL models* that can benefit from both effectiveness of DL and the prior knowledge encoded in physics-based bridge models. Such hybrid models are expected to outperform the DL-only models in terms of accuracy and efficiency; hence, enabling further enhanced bridge management. We elaborate on our specific research objectives toward this end in the next section.

Research Objectives

Despite their general success in a variety of application areas (including bridge management, as we described above), the success of even the state-of-the-art black box DL models is limited due to their large data requirements, inability to produce physically consistent results, and their lack of generalizability to out of sample scenarios. Given that neither a DL-only nor a physics-based-only modeling approach can be considered sufficient for complex engineering applications, the research community is beginning to explore the continuum between physics-based and DL models, where both engineering knowledge and data are integrated in a synergistic manner. This paradigm is fundamentally different from mainstream practices in the DL community for making use of domain specific knowledge, albeit in subservient roles, e.g., feature engineering or postprocessing. In contrast to these practices that can only work with simpler forms of heuristics and constraints, this approach explores a deeper coupling of DL methods with engineering knowledge.

With this proposal, we plan to build on our prior work in developing DL-only models for bridge management and introduce hybrid physics-based DL models with improved accuracy and efficiency, particularly for the bridge management task of *bridge deterioration forecasting*. Bridge deterioration forecasting models can be used to perform predictive analysis of the bridge performance 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.

We enumerate the specific objectives of our project as follows:

1. Design hybrid physics-based DL models for bridge deterioration forecasting;
2. Develop the designed hybrid physics-based DL models for bridge deterioration forecasting;
3. Evaluate the developed hybrid physics-based DL models using National Bridge Inventory (NBI) datasets;
4. Advance policy and practice with respect to bridge management by presenting the developed model to local and state governmental agencies (e.g., Colorado Department of Transportation, and City and County of Denver);
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>A. Methods for Design of Proposed Hybrid Physics-based Deep Learning Models for Bridge Deterioration Forecasting</u>: As mentioned above, in the past we have introduced various DL-only models for bridge subtyping and bridge deterioration forecasting. To develop the proposed hybrid physics-based method we will explore two families of methods to extend the DL-only models to hybrid physics-based DL models as follows.

1. Physics-Guided Learning

Engineering problems such as bridge deterioration forecasting often exhibit a high degree of complexity due to relationships between many physical variables varying across space and time at different scales simultaneously. Standard DL models can fail to capture such relationships directly from data, especially when provided with limited observation data. This is one reason for their failure to generalize to scenarios not encountered in training data. In the following, we discuss a number of ways researchers are beginning to incorporate physical knowledge into the learning process such that DL models can capture generalizable dynamic patterns consistent with established physical laws.

1.1 Physics-based Loss to Improve Predictions

One of the most common techniques to make DL models consistent with physical laws is to incorporate physical constraints into the loss function of DL models as follows[30]:

$$\mathrm{Loss} = \mathrm{Loss}_{\mathrm{TRN}}(Y_{\mathrm{true}}, Y_{\mathrm{pred}}) + \lambda R(W) + \mathrm{Loss}_{\mathrm{PHY}}(Y_{\mathrm{pred}})$$

where the training loss $Loss_{TRN}$ measures a supervised error (e.g., RMSE or cross-entropy) between true labels Y_{true} and predicted labels Y_{pred}, and λ is a hyper-parameter to control the weight of model complexity loss $R(W)$. These first two terms are the standard loss of DL models. The addition of physics-based loss $Loss_{PHY}$ aims to ensure consistency with physical laws. An added benefit is that training can include unlabeled data by omitting $Loss_{TRN}$.

1.2 Auxiliary Task in Multi-Task Learning

Multi-task learning frameworks allow for multiple learning tasks to be solved at the same time, ideally while exploiting commonalities and differences across tasks. This can result in improved learning efficiency and predictions for one or more of the tasks. Therefore, another way to implement physics-based learning constraints is to use an auxiliary task in a multi-task learning framework. This is shown to be successful in computer vision[31], but a physics-based analogue would be to have an auxiliary task representing consistency with physics-based principles. In this paradigm, a task-constrained loss function can be formulated to allow errors of related tasks to be back-propagated jointly to improve model generalization.

1.3 Physics-Guided Initialization

Since many DL models require an initial choice of model parameters before training, researchers have explored different ways to physically inform a model starting state. Poor initialization can cause models to anchor in local minima, which is especially true for deep neural networks. Transfer learning can effectively tackle this issue, where the pre-trained models from a related task are fine-tuned with limited training data to fit the desired task. One way to harness physics-based modeling knowledge is to use the physics-based model's simulated data to pre-train the DL model, which also alleviates data paucity issues.

2. Physics-Guided Design of Architecture

Although the physics-based loss in the previous section helps constrain the search space of neural networks during training, the neural network architecture is often still a black box. There are usually no architectural properties to implicitly encode physical consistency or other desired physical properties. A recent research direction has been to construct new physics-guided DL architectures.

2.1 Intermediate Physical Variables

One way to embed well-known physical principles into NN design is to ascribe physical meaning for certain neurons in the neural network by computing physically relevant intermediate variables in the neural pathway from inputs to outputs. For example, in a lake temperature modeling study Daw et al.[32] incorporate a physical intermediate variable in the LSTM architecture. This model produces physically consistent predictions in addition to appending a dropout layer to quantify uncertainty. Muralidhar et al.[33], a similar approach is taken to insert physics-constrained variables as the intermediate variables in the convolutional neural network (CNN) architecture and achieve significant improvement over state-of-the-art physics-based models on the problem of predicting drag force on particle suspensions in moving fluids.

An additional benefit of adding physically relevant intermediate variables in a DL architecture is that they can help extract physically meaningful hidden representation that can be interpreted by domain scientists. This is particularly valuable, as standard DL models are limited in their interpretability since they can only extract abstract hidden variables using highly complex connected structure. This is further exacerbated given the randomness involved in the optimization process.

2.2 Encoding Invariances

Common neural network design paradigms like the Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) have revolutionized the ability of DL algorithms by implicitly encoding time invariance into the RNN architecture and spatial translation, rotation, and scale invariance into the CNN. In the same way, engineering modeling tasks such as bridge modeling require other invariances based on physical laws. For example, in turbulence modeling and fluid dynamics, recent work defines a tensor basis neural network to embed the fundamental principle of rotational invariance into a neural network for improved prediction accuracy[34]. This solves a key problem in DL models for turbulence modeling because without rotational invariance, the model evaluated on identical flows with axes defined in other directions could yield different predictions. This work alters the neural network architecture by adding a higher-order multiplicative layer that ensures the prediction lies on a rotationally invariant tensor basis.

2.3 Physics-Guided Neural Architecture Search

Currently employed architectures primarily have been developed manually by human experts, which can be a time-consuming and error-prone process. Because of this, there is growing interest in automated neural architecture search methods[35]. A young but promising direction in DL architecture/model design is to embed prior physical knowledge into neural architecture searches. Ba et al.[36] add physically meaningful input nodes and physical operations between nodes to the neural architecture search space for the search algorithm to discover more ideal physics-guided DL architectures.

<u>B. Software for Development of Proposed Tools</u>: We will develop the proposed hybrid physics-based DL models for 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.

C. Test Data for Evaluation of Proposed Tools: We plan to use the datasets stored and maintained at the National Bridge Inventory (NBI)[1]. As an example of typical NBI bridge inspection dataset, the City of County of Denver (CCD) dataset covers 208 bridges, 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).

D. 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.

Expected Outcomes

The expected outcomes of this work include:

1. Novel hybrid physics-based deep learning models for bridge deterioration forecasting; these models will also likely inspire more research in this area that can generate physics-based deep learning models for other bridge management tasks;
2. Education materials on the topic of data-driven bridge management with a focus on physics-based deep learning models;
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 physics-based deep learning models for bridge deterioration forecasting can be implemented as software tools. These software tools can be offered to governmental agencies for their daily use, potentially resulting in significant improvement in effective bridge deterioration forecasting 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

[1] National Bridge Inventory: https://www.fhwa.dot.gov/bridge/nbi.cfm

models 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 Rens'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, civil engineering, 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, CCD, and NREL) 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 Rens) 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 models 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 Hybrid Physics-based Deep Learning Models for Bridge Deterioration Forecasting												
Developing Hybrid Physics-based Deep Learning Models for Bridge Deterioration Forecasting												
Evaluating Hybrid Physics-based Deep Learning Models for Bridge Deterioration Forecasting												
Incorporating lessons into graduate courses												
Advancing Policy, Practice and Research by Dissemination / Technology Transfer												

Project Cost

Total Project Costs: $120,000
MPC Funds Requested: $ 60,000
Matching Funds: $ 60,000
Source of Matching Funds: University of Colorado Denver, in-kind support

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