Storm Surge Prediction with Integration of Physical Knowledge in Machine Learning Models

Name: Sambit Bhattacharya

Hosting site: DHS Coastal Resilience Center

Mentor: Brian Blanton

Mentor Signature: ___Brian O. Blanton_____Renaissance Computing Institute, UNC-CH, DHS CRC

Abstract

Modeling complex systems with governing physical equations is difficult in many areas due to computational challenges. Current research in Artificial Intelligence and Machine Learning (AI/ML) has produced evidence that data-driven learning algorithms can excel at tasks like classification and prediction where there is no known overarching mathematical model, e.g. in applications like computer vision and natural language processing. An emerging area of research suggests that scientific prediction can also benefit from data-driven AI/ML. However, this optimism is tempered by experimental challenges which indicate that exclusive reliance on historical data without inclusion of physical knowledge does not work well in practice. While at this early stage of research we do not yet have unifying frameworks for integration of physical knowledge with data-driven approaches, researchers working in different applications have discovered mathematical and computational tools that create effective solutions. It is hypothesized that the storm surge prediction problem may also benefit from such an integrated approach. We describe research on constraining an Artificial Neural Network (ANN) with a physics-based loss function that penalizes the ANN when it deviates from prediction patterns that would normally be expected from the input data of water level time series. This is an initial step in a new approach to the problem of storm surge prediction. With additional research to include geospatial constraints, knowledge of distribution shift over time in water levels, and wind velocity field, we may begin to see reduction in computational time without sacrificing accuracy when used alongside established numerical programs like ADCIRC. Increasing the speed of storm surge prediction can be highly beneficial to society and the mission of DHS since it can save lives and property in exposed areas.

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1. Introduction

Modeling complex systems that address problems in cross-disciplinary phenomena is challenging. In some cases, where governing physical equations are unknown, model building becomes difficult. Even if a model is derived correctly, solving it may not be possible or may need a great amount of computational resources which renders it impractical. In contrast, data-driven methods discover underlying principles from data without any knowledge about the governing equations. Although training time tends to be very high, these models e.g. deep learning neural networks produce outputs from inputs (known as inference time) within very short time limits. An emerging area of Artificial Intelligence and Machine Learning (AI/ML) is the research to develop methods that can guide machine learning with established theory and knowledge of facts. Terms like theory-guided machine learning or physics-guided machine learning have been used in the literature [1] for this emerging area of research. Although there is no common agreement on using such terms and other researchers may use different terminology, the broad agenda is to improve data-driven approaches with knowledge gained by other methods. These other methods can be scientific theory and equations, or knowledge bases which include ontologies and facts.

The Summer Research Team (SRT) of 2020 from Fayetteville State University, consisting of students Grace Vincent and Raymond Kimble, and professor Sambit Bhattacharya, worked on the problem of storm surge prediction with integration of physical knowledge in AI/ML models. This work was done under the mentoring of Dr. Brian Blanton, a researcher in the Coast Resilience Center. A storm surge is rise in water level that occurs independent of normal tidal patterns and is caused by the approach of a tropical storm or hurricane near the coast. It is generated by atmospheric forcing that is associated with storms, in particular by the complex physical interactions of drag of the wind on the sea surface and by variations in the surface atmospheric pressure associated with storms [11]. ADCIRC, a system of computer programs which utilizes finite element methods for solving time-dependent equations in two and three dimensions, is applied to the problem of storm surge prediction [10]. This SRT project is inspired by recent progress in application of AI/ML to scientific problems [6, 9, 12] which suggest that there are significant gains in using data-driven AI/ML alongside numerical methods. These gains are generally in the form of computational speed-up without sacrificing predictive performance. Decreasing the time needed to generate predictions is of practical importance in the storm surge problem, so research in application of AI/ML to the storm surge problem can potentially benefit scientific research and the operations that are supported by research.

The author has many years of experience in research in AI/ML. While AI/ML has a rich theory, the author is interested in use-inspired projects where existing problems can be solved using the data-driven modeling insights that AI/ML creates. Having lived in North Carolina for more than a decade he has first-hand experience of the devastating effects of storms and wishes to contribute to scientific efforts that may save lives and property. He is committed to education and learning, and strongly believes that the SRT research experience has been beneficial to his work on improving course-based education at his home institution. The author will use ideas and use-case inspired by the SRT experience to create hands-on project-based learning modules for the Artificial Intelligence courses that are his recurring teaching assignments. Since this work is new and part of an emerging and rapidly progressing area, he will submit a follow up proposal to the US Department of Homeland Security for continuation of the research.

2. Description of the Research Project

In machine learning, the importance of prior knowledge can be seen from the No Free Lunch theorem [8] which states that all the algorithms perform the same when averaged over the different problems and thus implies that to gain in performance one must use a specialized algorithm that includes some prior knowledge about the problem at hand. The process of integrating prior knowledge into the machine learning pipeline can be divided into three stages [7] and each of these stages has a key question: (1) What kind of **knowledge source** is integrated? (2) How is this **knowledge represented**? (3) Where is the **knowledge integrated** in the machine learning pipeline? The research and this initial report on integration of physical knowledge in machine learning for storm surge prediction, is guided at a high level by this taxonomy [7]. Based on literature review and discussions with experts, it is the opinion of the author that this is the **first attempt** to apply a hybrid of prior knowledge and data-driven machine learning to improve the prediction of storm surge.

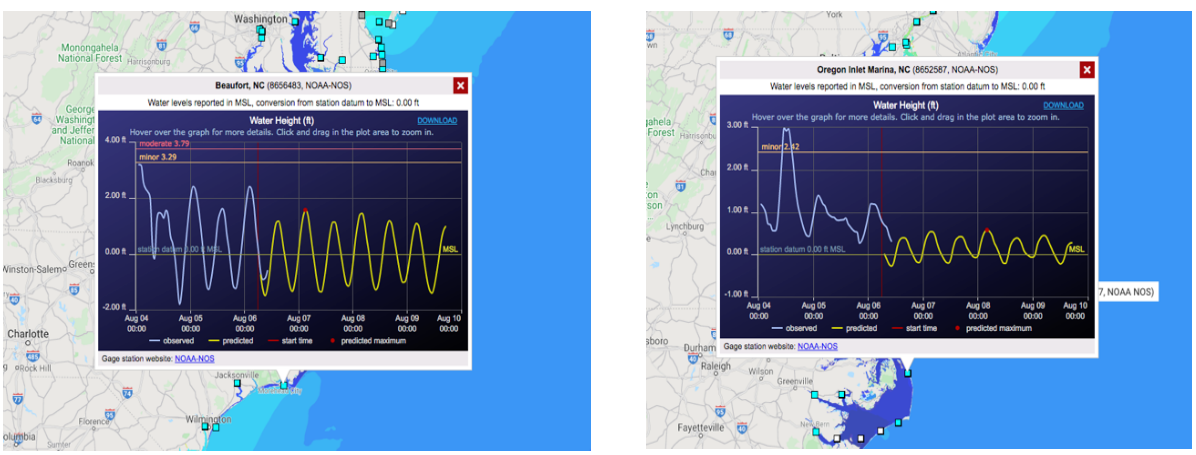

Figure 1: Examples of prediction of Maximum Water Height above Mean Sea Level (MSL) by the ADCIRC model from the Coastal Emergency Risk Assessment (CERA) site. The blue colored part of the plot represents real observations and the yellow colored portion represent predictions. The task of predicting this value is more challenging due to presence of land mass before open ocean (right image) versus only open ocean (left image).

Knowledge Source: Analytical equations and numerical models are used to describe storm surge in the literature. These equations and numerical algorithms attempt to model surge events that arise from the complex interaction of the drag of wind on the sea surface and variations in the surface atmospheric pressure associated with storms. Topographic features and bathymetry have a significant role in these computational approaches that require high performance hardware to generate predictions within specified time limits. Figure 1 shows real data and prediction over different geographic locations along the North Carolina coast illustrating the challenges inherent to the numerical modeling of such complex phenomena. Prediction of storm surges started with the fitting of non-linear equations to find the storm surge. Increases in accuracy were achieved by studying historical data over long periods of time. Geometry of the coast beneath the sea, as well as the coastline shape have significant effect on the surge [4]. The types of lands (coastlines, marine vegetation, marshlands, wetlands) that storm surges hit also have an impact on the severity of the storm surge. In addition to these, man-made structures have a direct effect on the storm surge impacts as some areas can pool the water from the surge causing water to be trapped. The impacts of Hurricane Katrina on the Louisiana coast have enhanced our understanding of these effects and created more knowledge for model building [14]. Some activities during the summer SRT project centered around studying literature to select the most useful knowledge sources that would be useful for building AI/ML models. As described later in knowledge integration, the ongoing attempt in this new research approach is to use data to train an Artificial Neural Network (ANN) so as to constrain it with physical knowledge. Knowledge of astronomical tides, surge patterns and noise of water levels was used as shown in Figure 2, with accounting of topography and bathymetry being more advanced and continuing effort in this work.

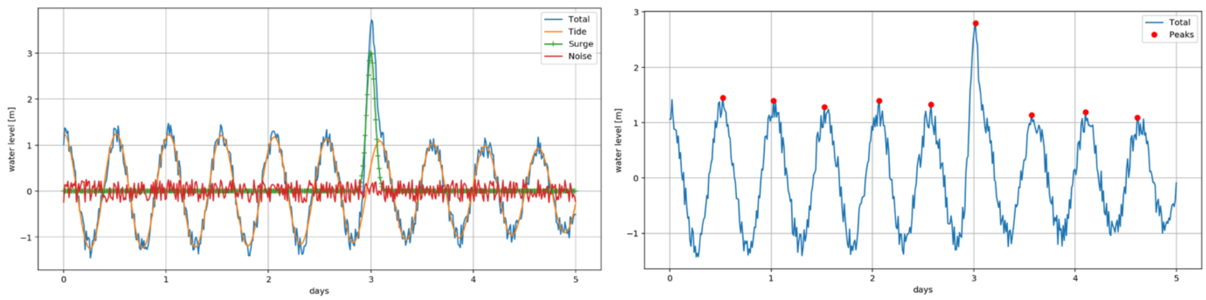

Figure 2: Time series of synthetic water levels over five days. The water level is a combination of astronomical tide, noise, and surge (the peak around day 3). The image on the right shows the peak finding method which is able to numerically determine the location of water level peak in the time series data.

Knowledge Representation: Physics-guided machine learning is emerging as a new paradigm for modeling and scientific discovery that combines scientific theory with data science techniques such as machine learning [1, 2, 3, 6, 9, 12]. Traditionally, theory-based models of physical processes have served as the foundation for both academic research and operational best practices in storm surge prediction. More recently, with advances in sensor technology, data-driven techniques have the potential to become more useful. In recognition of the limitations of solely data-driven models with respect to generalizability and physical interpretability, a new approach in physics-guided machine learning was proposed in the SRT project and initial work was done based on this proposal. These models use physical principles to inform the search for the best machine learning model, thereby capturing the best attributes of both physics-based and data-learning models, as shown in Figure 3 below, where the general approach and the specific method used in the SRT project are both illustrated.

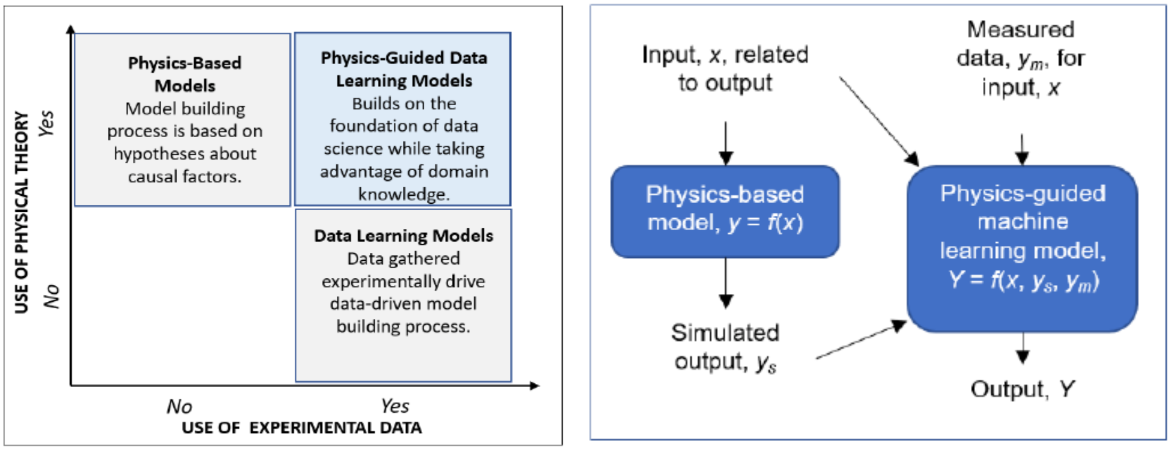

Figure 3: Illustration (left image) of how purely physics-based models and data-driven/data-learning models (i.e. models that learn only from data) are combined to produce hybrid models and one method (right image) of creating physics-guided machine learning model – an approach that was used in the SRT project. From Greis, Nogueira, Bhattacharya and Schmitz [3].

Data-driven approaches such as statistical models and machine learning are built on historical and/or real-time data and can learn directly from sensor data. Advantages include the ability to model highly complex physical systems for which there is no underlying physical model that completely defines the system, or where the relationships between the input and output variables are difficult to describe using physics, or when the ability to include contextual data (e.g. geospatial data such as topography and bathymetry) is important. A challenge with data-driven (black box) models is that they are agnostic to physical laws because they rely only on data. They are therefore dependent on data quality which can lead to relationships that do not generalize beyond the training data set. Data-driven model predictions are subsequently limited to the training data range and cannot, in general, be used for generating new scientific knowledge. Physics-based models such as ADCIRC are still preferred for scientific discovery. However, especially for highly complex physical systems, obstacles to their implementation include: 1) every model is an approximation of reality; 2) the model input parameters require identification, estimation and calibration; and 3) the model may be more complex and computationally intensive than required. This research addresses the modeling of storm surge where data is often limited by cost of acquisition or time constraints but for which the underlying physical models are often more specific.

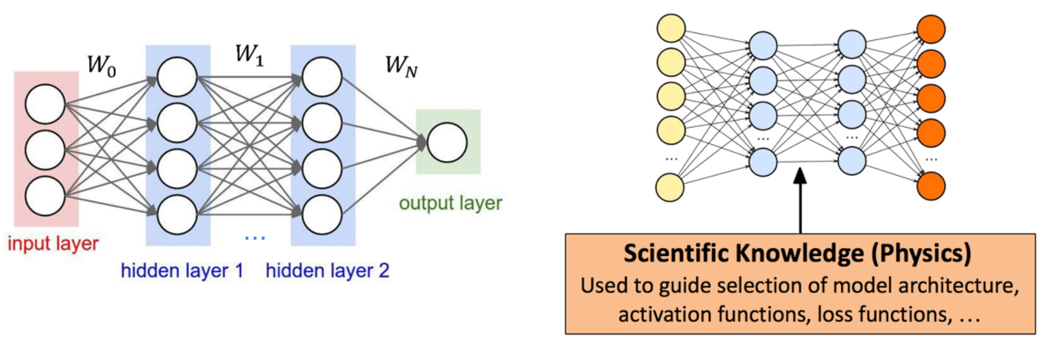

Figure 4: The building blocks of an Artificial Neural Network (ANN) consist of neuronal layers where neurons are connected by mathematical weights that are tuned during "learning" (left image). Inclusion of scientific knowledge creates additional constraints on these learned weights so that the ANN is able to generate predictions that are physically correct (right image).

Knowledge Integration: The development of the physics-guided machine learning approach is summarized below.

Step 1: A multi-layer perceptron (MLP) architecture was created. This architecture is similar to the one shown on the left image of Figure 4. A few separate architectural specifications consisting of different numbers of hidden layers, and width of the layers were experimented with.

Step 2: Generate training data from the physics-based simulation model as shown in Figure 2. The simulation generates water level as a combination of astronomical tides, noise and storm surge. The local peaks of the water level time series are computed using a peak finding method used in signal processing. The time measured between consecutive peaks provides an estimate of the periodic behavior of the water level.

Step 3: Train the physics-guided MLP with the simulation data and physics-guided constraint. The physics-guided constraint is an added term to the loss function for the MLP where the general loss function is a combination of training loss and standard regularization terms which are weighed with constants.

$$\text{Loss Function} = \text{Training Loss}\left(Y,\hat{Y}\right) + \lambda_1 \|W\|_1 + \lambda_2 \|W\|_2$$

This loss function is further enhanced by adding a physics-based loss term.

$$\text{Loss Function} = \text{Tr. Loss}\left(Y,\hat{Y}\right) + \lambda_1 \|W\|_1 + \lambda_2 \|W\|_2 + \lambda_{\mathrm{PHY}}\, \textbf{Physics-based Loss}$$

The physics-based loss used was the standard deviation of the periodicity of the water level as estimated from the peak-to-peak time intervals. This works well in practice for basic patterns of water level time series since the physics-based loss penalizes the neural network when it predicts variability in the time period. In this case the time series can be assumed to exhibit an almost constant periodicity. Future work will address distribution shift where the complex harmonics, including storm surge can change the pattern over time. Physical constraints arising from geospatial effects, effect of the wind velocity field are advanced research topics which should be explored in future research.

Step 4: Generate results, measure accuracy of prediction. After training the physics-guided MLP with simulation data, tests were done to measure the accuracy of prediction. These tests consisted of providing the MLP with some initial measurements of the water level time series as input, with the output being the MLP's estimate of the water level over future time points. The SRT project came to a conclusion while work was being done on this step, however tests indicate that the physics-based loss function developed in step 3 works well in practice for simulated data in basic scenarios.

3. Contributions Made to the Research Project

The author contributed to the research project by developing the overarching research plan with mentoring of Dr. Blanton, by mentoring students from his university in creating code and data-driven experiments, by selecting approaches from the literature which are potentially useful in this work, creating research plans to extend these existing approaches, and also by writing code and performing experiments together with students. His experience in the area of AI/ML, Computer Science, and practical aspects of software engineering helped bring important knowledge of algorithms, coding and data-driven experiments into this SRT project. He organized meetings with students where the objectives of this meeting were to troubleshoot code the students had written, to create steps for the next stage of code development, and to select experiments based on data. He met weekly with Dr. Blanton and students to create research plans and to present current progress, and he also wrote weekly reports that were submitted to DHS and ORISE.

The author contributed practical knowledge in PyTorch [13] which is a free and open-source machine learning library. PyTorch was created for the Python programming language but also includes support for C, C++ and Tensor computing. In accordance with common software engineering practice in PyTorch he created the following structure of the software for the project: (1) model/net.py for specifying the neural network architecture, the loss function and evaluation metrics (2) model/data_loader.py to specify how data should be fed into the network (3) train.py to contain the main training loop (4) evaluate.py to contain the main loop for evaluating the model and (5) utils.py to the contain the utility functions for handling hyperparameters, for logging and storing models. He also worked with students on data parallelism in PyTorch which increases efficiency by enabling the division of the data into batches, which are then sent to multiple General-Purpose Graphics Processing Units (GPGPUs) for processing. Using this technique, PyTorch can shift a significant chunk of the workload from CPU to GPU, which is one of the most effective ways of increasing efficiency when training neural networks. The author also contributed by preparing the high-performance computing cluster at his home institution for use by the SRT students. He also worked with the students to access and use the computing resources provided by the CRC.

4. Skills and Knowledge Gained

The author gained knowledge of the application domain i.e. storm surge prediction during the weeks of the SRT program. This knowledge was gained through discussions with mentor Dr. Brian Blanton and by reading research articles shared by him. It is extremely important for a researcher in AI/ML to gain knowledge of other domains that may need solutions developed using AI/ML techniques. The SRT experience was enriching for the author because it introduced him to a scientific domain which has challenging problems and is of great benefit to society. During the project the author also read recent publications in AI/ML which is significant work since this is a rapidly developing area with thousands of articles published each year in top conferences. His effort was to select the most relevant publications and to create a roadmap for future research, and this roadmap will be included in the follow up proposal to DHS.

5. Research Experience Impact on My Academic Career Planning

As a tenured professor in a primarily teaching institution, where research activities are being increasingly supported by the administration, the author will be able to bring back knowledge and expertise that will benefit the institution. He will share knowledge of the DHS SRT opportunity with other professors and students during university meetings with the expectation that other faculty and student teams will be encouraged to apply for SRT funding. The author will use ideas and use-cases inspired by the SRT experience to create hands-on project-based learning modules for the Artificial Intelligence courses that are his recurring teaching assignments. Since this work is new and part of an emerging and rapidly progressing area, he will submit a follow up proposal to the US Department of Homeland Security for continuation of the research. In collaboration with Dr. Blanton and the CRC, the author will apply for funding to other agencies like the National Science Foundation. These follow up activities are expected to have high impact on the research and teaching capabilities of the author and the university he works for.

6. Relevance to the mission of DHS

The vital mission of the US Department of Homeland Security is to secure the nation from the many threats we face. Coastal hazards like storm surge expose the coastal areas of the US to risk of property damage, loss of life and environmental degradation. The unexpected rise of sea level can cause significant flooding and cost people their lives. Powerful winds are not the only deadly force during a hurricane - the greatest threat to life actually comes from the water in the form of storm surge. Millions of US citizens reside in coastal areas and increase in this population and economic activity in coastal areas creates new forms of exposure to risk for the nation as a whole. The impact of past storm surge events created by Floyd (1999), Katrina (2005), Rita (2005) and Irma (2017) is measured in hundreds of billions of Dollars. Even though we cannot completely avoid the effect of this hazard, we can reduce the impacts of hazard by scientific study of how the event occurs which will increase our ability to predict storm surge level in the areas under exposure. This increased ability will help and implement disaster management plans with enhanced preparedness and mitigation strategies, thus developing the resilience of society towards coastal hazards.

7. Acknowledgements

The author wishes to thank the Coastal Resilience Center, Oak Ridge Institute for Science and Education, and the Department of Homeland Security for supporting the SRT project. CRC researcher Dr. Brian Blanton was an extremely helpful mentor who provided research guidance and was very understanding of the many challenges the SRT team from FSU faced during the time of Covid-19. Attending meetings on zoom was the only option available during a raging pandemic and the team's ability to make progress was largely dependent on the support received from Dr. Blanton. The author also wishes to the thank the entire DHS and ORISE team consisting of Rick Luettich, Thomas Richardson, Robert Whalin, Anna Schwab, Beth White and others. The SRT team project would not have been possible without the hard work and dedication of these individuals.

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