Deep Learning for Accelerated Reliability Assessment of Transportation Networks

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INTRODUCTION

What is hazard reliability?
Hazard reliability for an infrastructure system is defined as the degree of assurance that the system will continue to successfully operate at a desired level of performance during a certain period of time and in a specified environment in the aftermath of a hazard.

Importance
Assessment of the impact of natural disasters on the infrastructure systems is of importance towards the four main phases of emergency management:

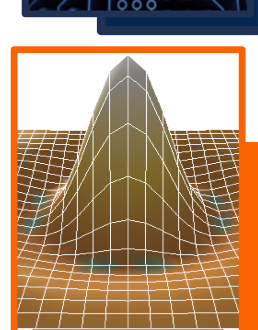
Challenges
Hazard reliability assessment of large and complex infrastructure systems is challenging due to:

- Large number of network components
- Computational Complexity
- Uncertainties in hazard models
- Complex network topology
- Statistical dependence between component failures

OBJECTIVE

The objective of this study is two-fold:

Accelerate the reliability assessment of large transportation systems by utilizing deep-learning-based surrogates.

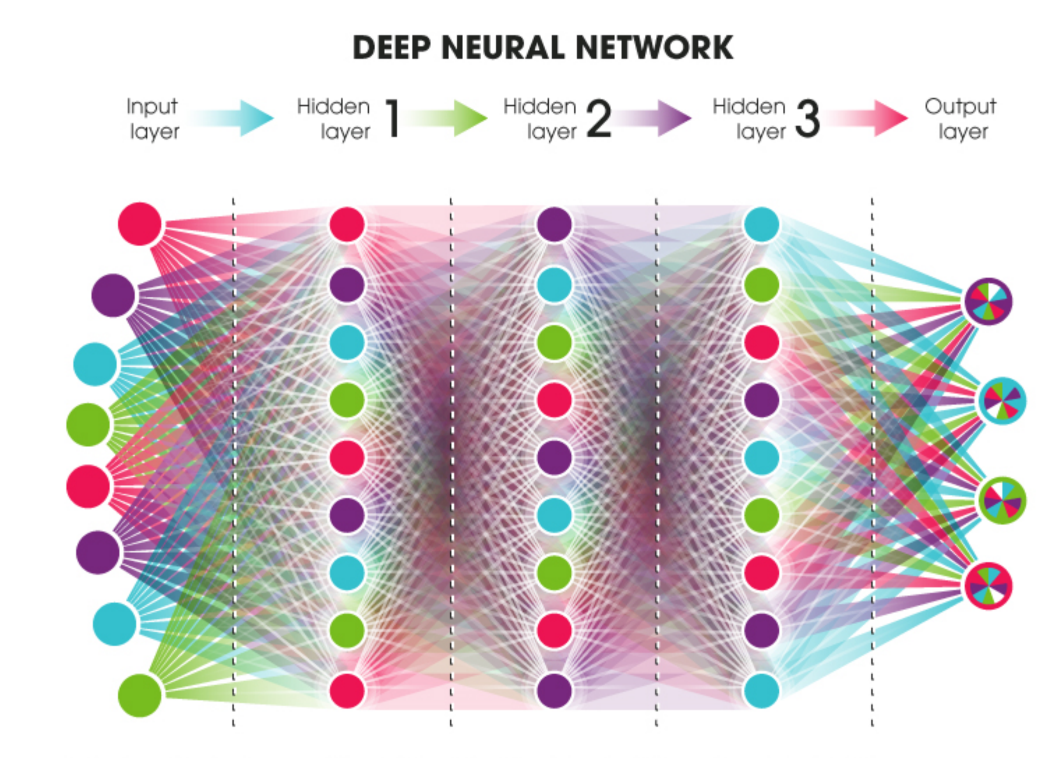


Perform reliability analysis of transportation systems considering seismic model uncertainties in order to enhance the accuracy of predictions.

PROBLEM DESCRIPTION

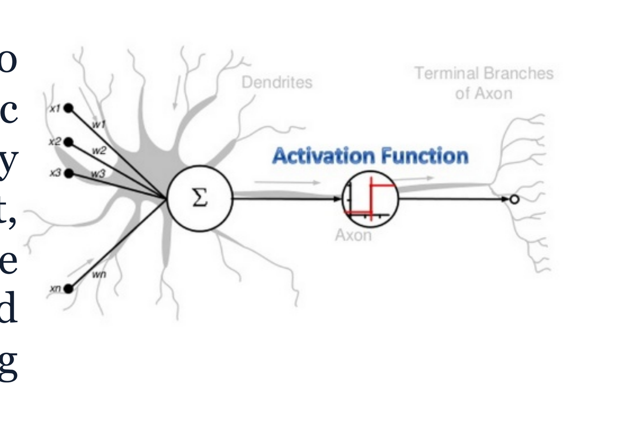
DEEP NEURAL NETWORKS

A deep neural network consists of one input, one output and multiple fully-connected hidden layers. Each layer is represented as a series of neurons and progressively extracts higher and higher-level features of input until the final layer makes a decision about what the input shows. The more layers the network has, the higher- level features it will learn.



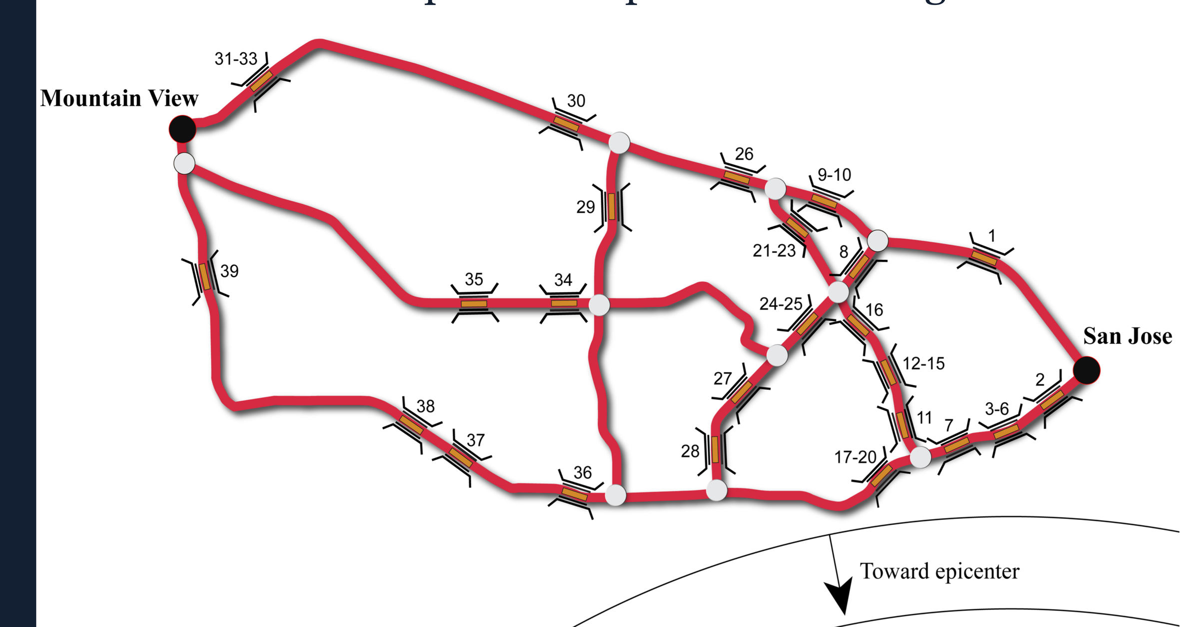
An artificial neuron contains a nonlinear activation function and has several incoming and outgoing weighted connections.

Neurons are trained to filter and detect specific features or patterns by receiving weighted input, transforming it with the activation function and passing it to the outgoing connections.

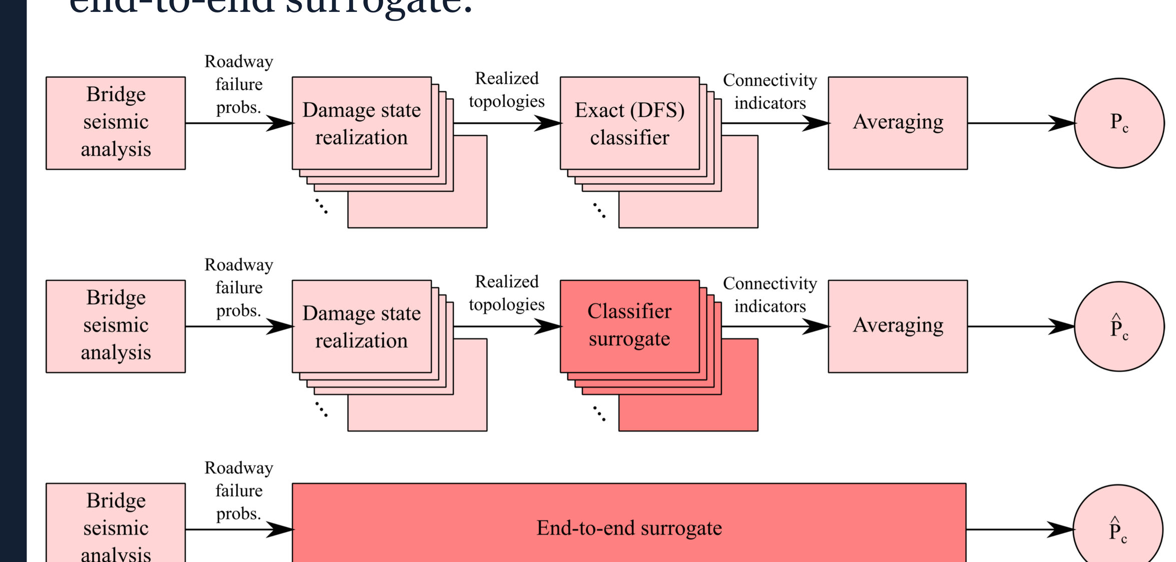


CASE STUDY

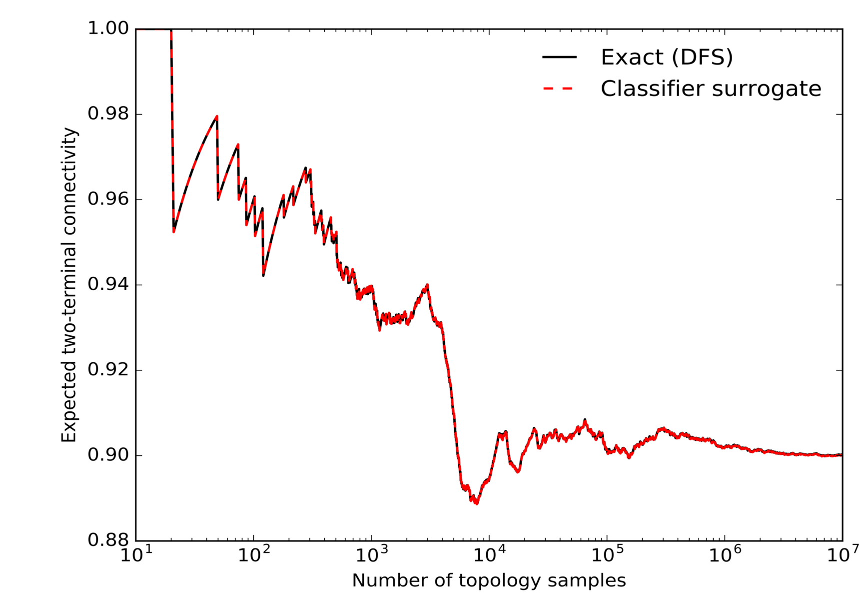
We consider the two-terminal reliability of the San Jose-Mountain View transportation network, subject to 1989 Loma Prieta earthquake with probabilistic magnitudes.



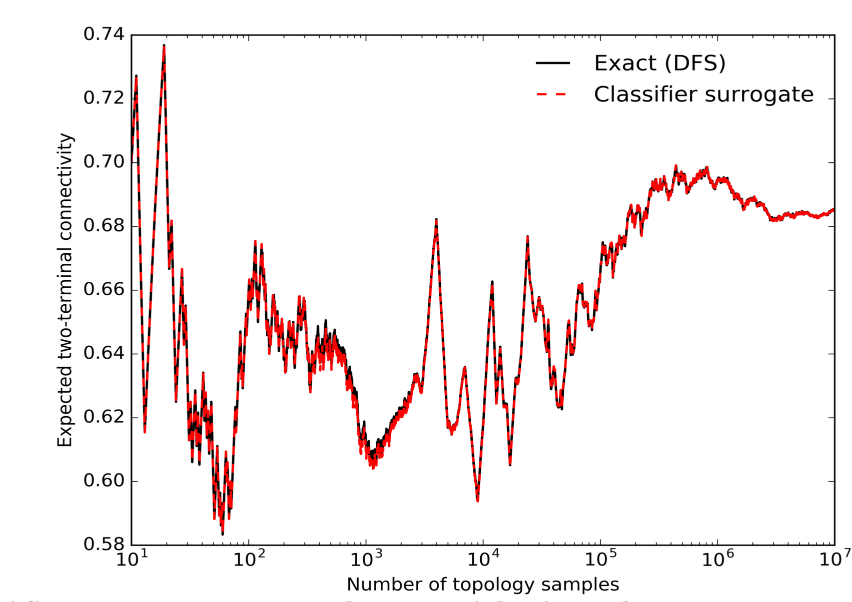
Two-terminal connectivity is relevant when, for instance, the accessibility from a major attraction point to a major hospital, or from a feedstock to demand zones, is to be maintained. The figure below shows the general workflow for calculation of the expected two-terminal reliability, using the standard procedure, classifier surrogate, and end-to-end surrogate:



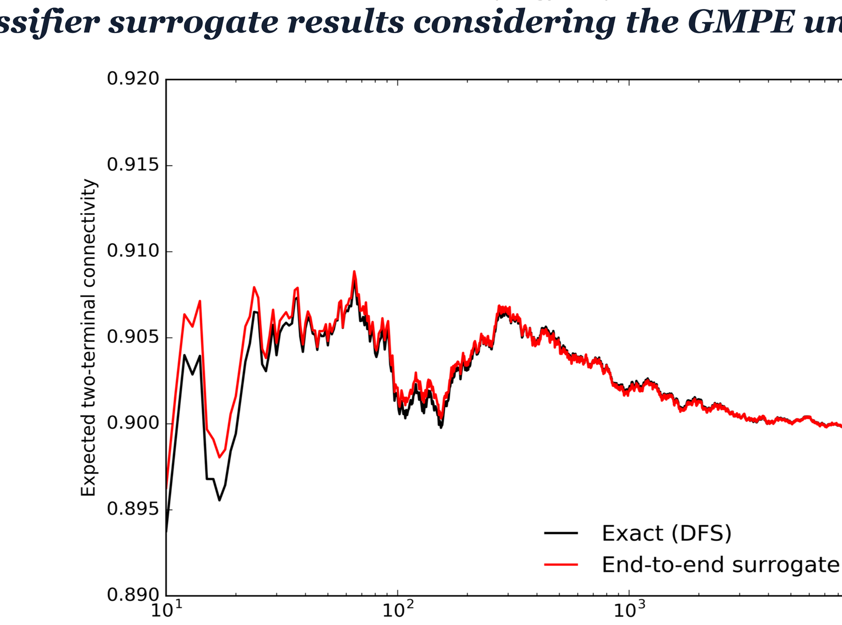
RESULTS



Classifier surrogate results for earthquakes with probabilistic magnitude (ranging between 6.9-7.4 Mw).



Classifier surrogate results considering the GMPE uncertainties.



End-to-end surrogate results for earthquakes with probabilistic magnitude (ranging between 6.9-7.4 Mw).

CONCLUSION

We studied deep-learning-based surrogates and, in a case study, highlighted how they can offer fast infrastructure response computations with high accuracy. It is shown through a comprehensive case study that:

- the classifier and end-to-end surrogates can provide, respectively, at least 6-fold and 20-fold reduction in computational time, including the time needed for surrogate training.
- This saving is even more substantial when trained models are to be used repeatedly when e.g. reliability analysis for a range of magnitudes and correlation structures or a sensitivity analysis is pursued.

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