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Department of Civil and Environmental Engineering
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Deep Learning for Accelerated Seismic Reliability Analysis of Transportation Networks

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- Case Study: Bay Area
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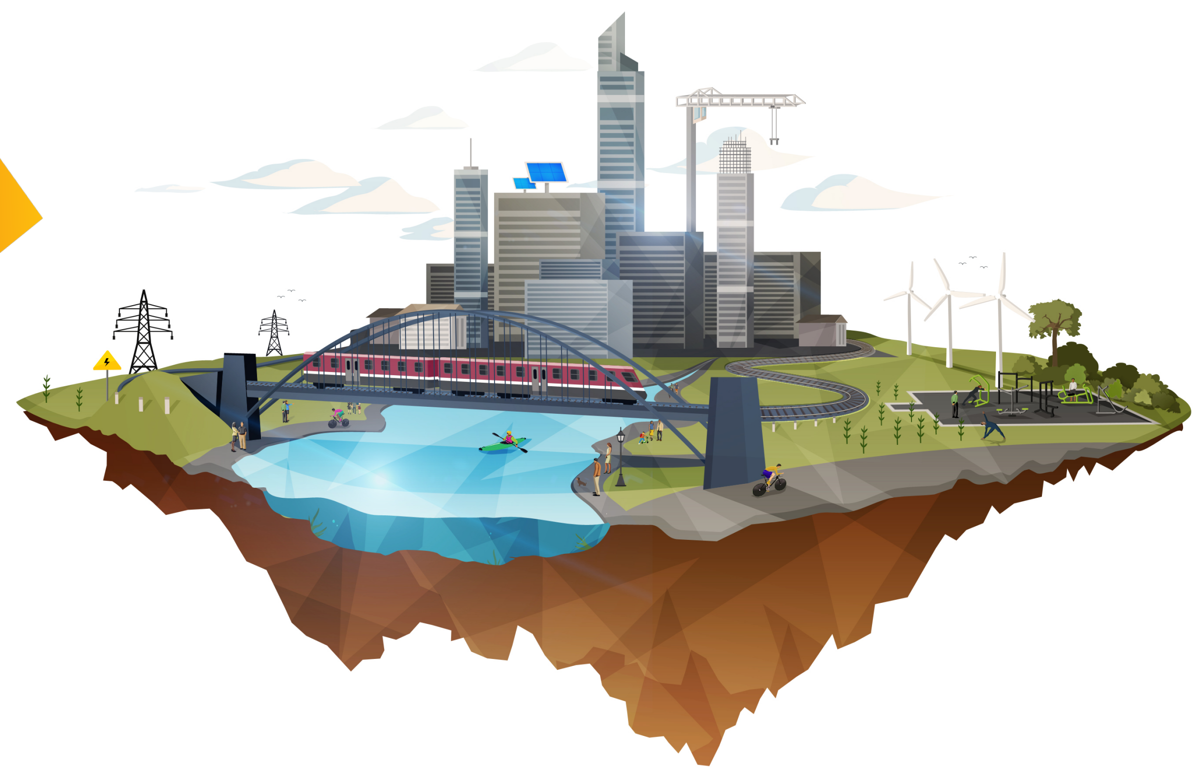
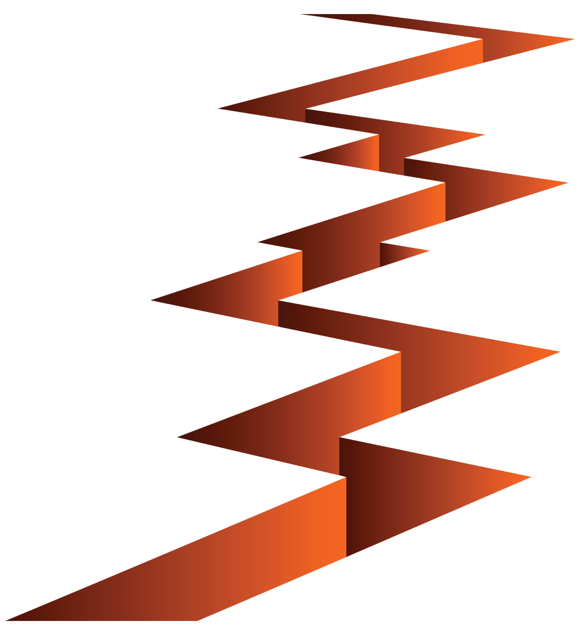
1. INTRODUCTION AND MOTIVATION

Problem Statement



STEP 2



STEP 1

STEP 3

The Three Steps of Reliability Analysis

STEP 1: Ground Motion Intensity Evaluation

- Including evaluation of Peak Ground Acceleration (PGA), Spectral Acceleration (SA), and Peak Ground Velocity (PGV) at site locations.

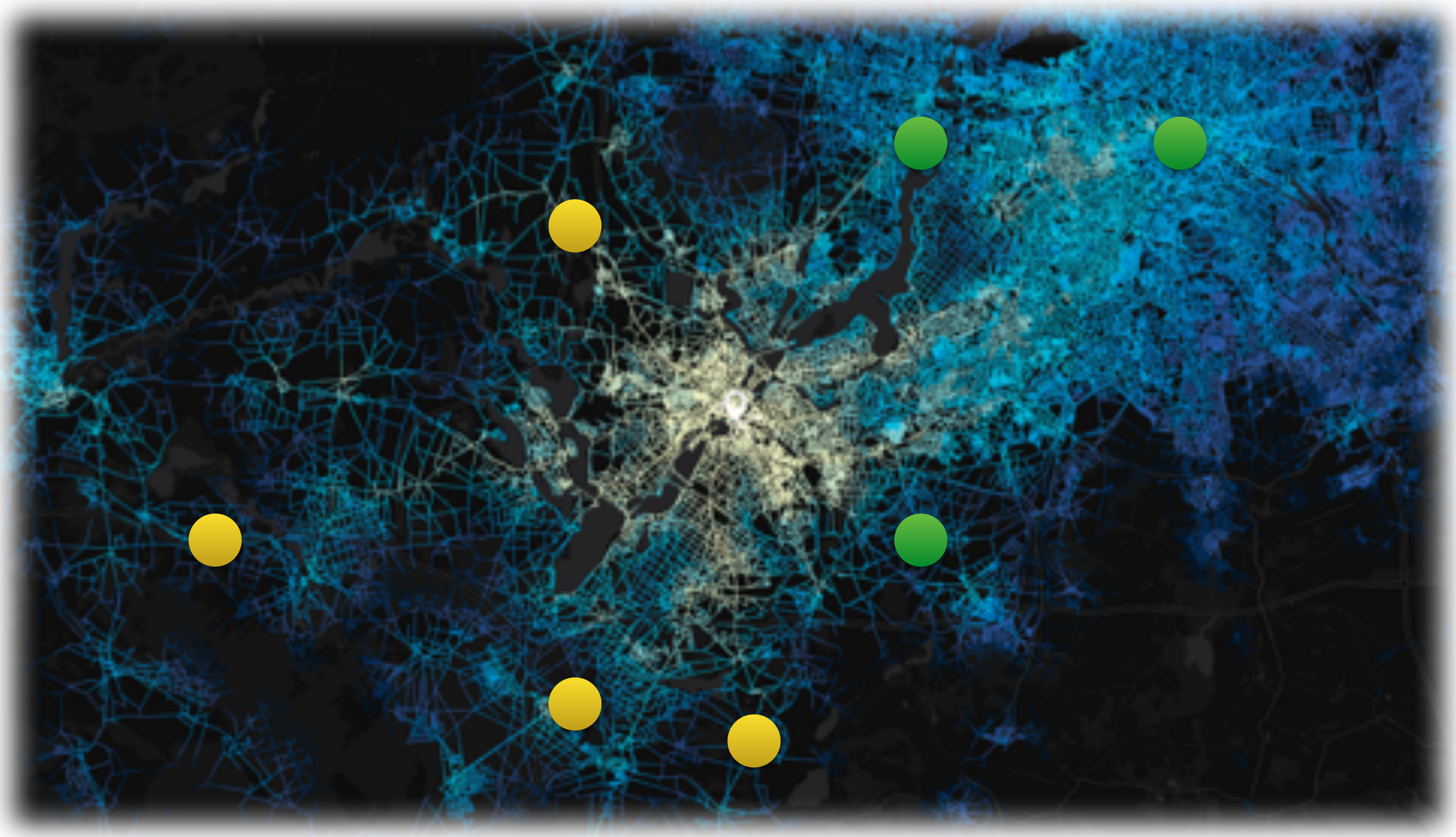
STEP 2: Component-Level Response

- Including evaluation of the probability of damage states of bridges, roadways, and pavement.

STEP 3: System-Level Response

- Examples include:
  - Percentage of bridges damaged
  - Weighted shortest path
  - Fixed-demand travel time
  - Terminal connectivity
  - Morning or evening peak commute time

K-Terminal Reliability



Source Node

Terminal Node

$$g\left(x_1^{(j)}, \ldots, x_\ell^{(j)}\right) = \begin{cases} 1, & \text{if } v_i, v_j \text{ connected } \forall v_i \in \mathbf{V}_s \\ 0, & \text{otherwise,} \end{cases}$$

$$\hat{P}_c = \frac{1}{N} \sum_{j=1}^{N} g(x_1^{(j)}, x_2^{(j)}, \ldots, x_\ell^{(j)})$$

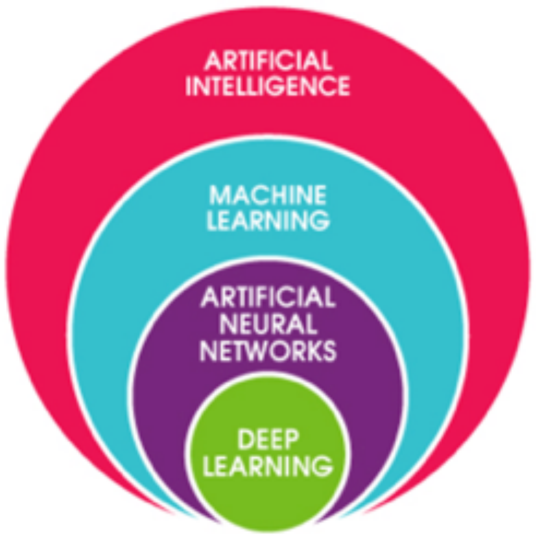
Importance of K-Terminal Reliability

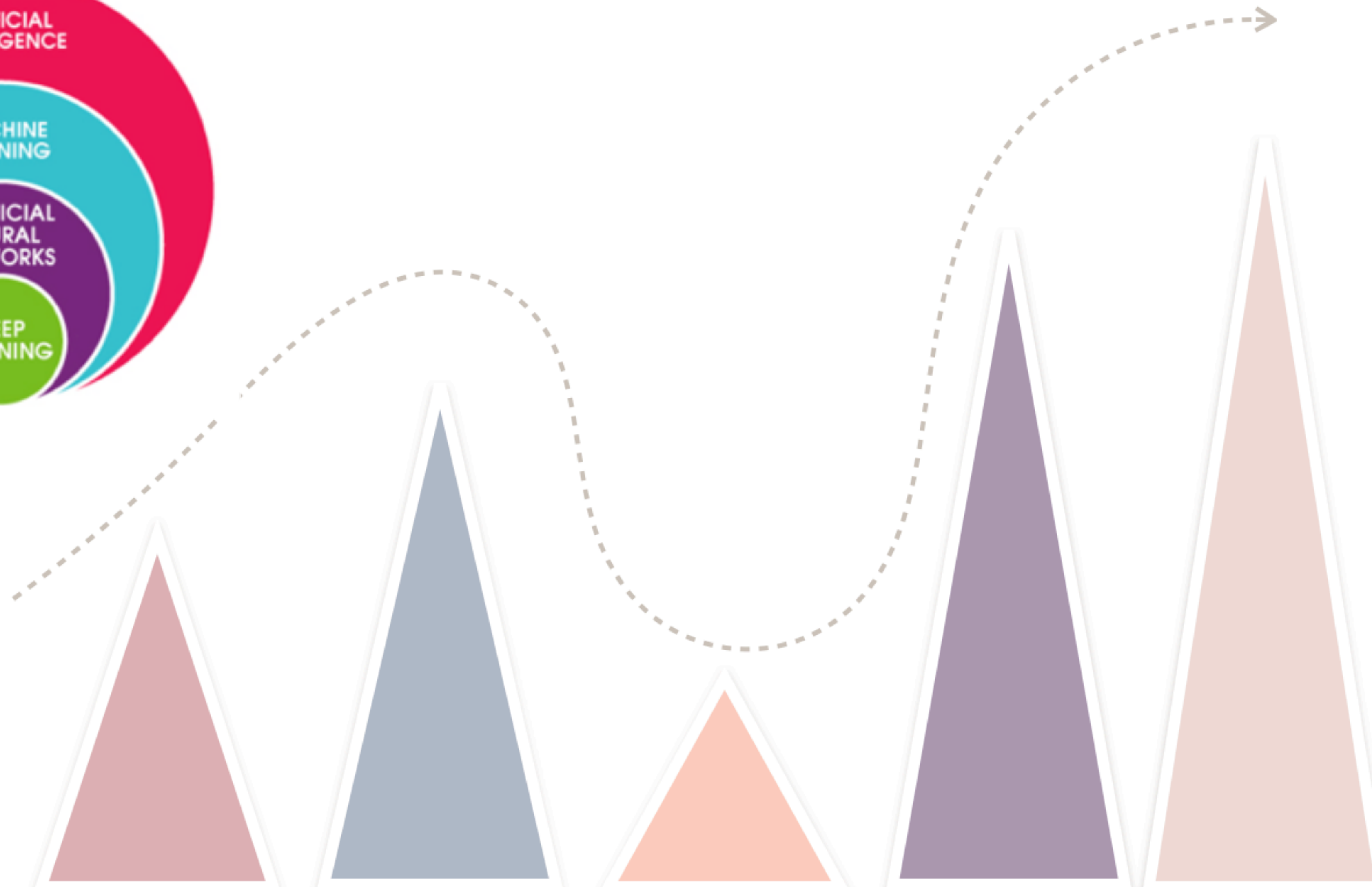
The k-terminal reliability is important, for instance, for:

- Evacuation Purposes
- Maintaining accessibility form a major attraction point to a major hospital
- Maintaining accessibility from a feedstock to demand zones

2. INTRODUCTION TO DEEP LEARNING

History





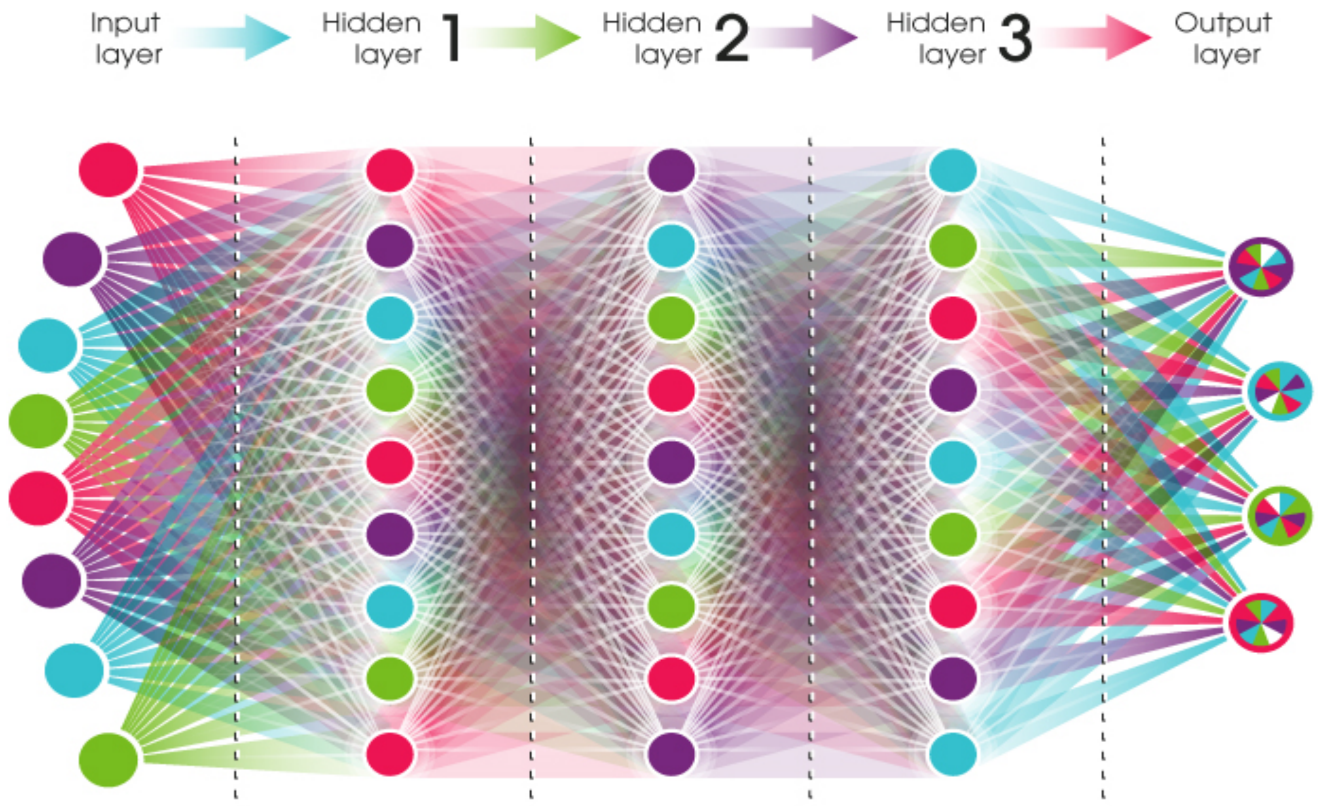
1980	1990	2000	2010	PRESENT
Start of Neural Networks	**Lots of Pogress**	**NN Disappeared because of slow computers and tiny datasets**	**Big Come-Back because of GPUs and big Data**	**Numerous Real-World Applications, e.g. Autonomous Vehicles**

What is a Deep Neural Network?

A deep neural network consists of one input layer, one output layer, and multiple 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 [1,2].

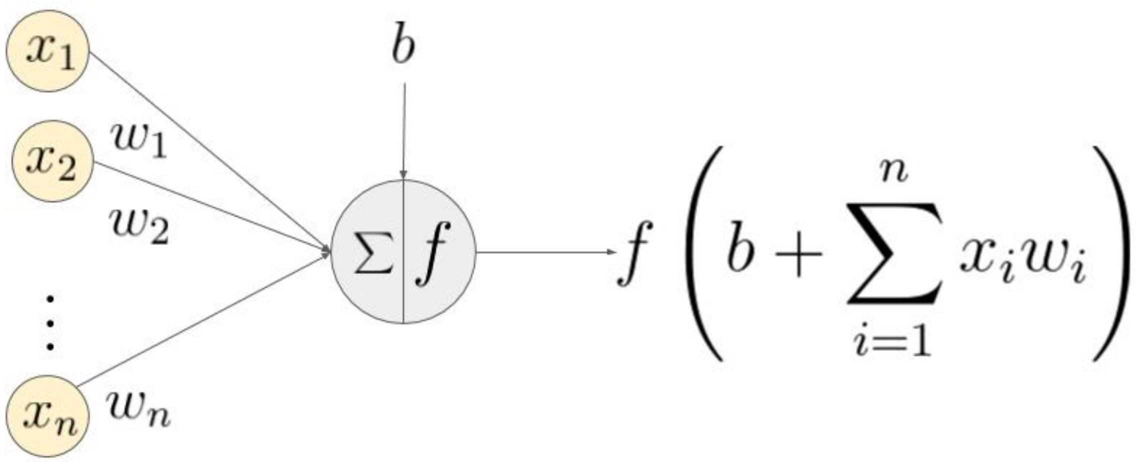


neuralnetworksanddeeplearning.com - Michael Nielsen, Yoshua Bengio, Ian Goodfellow, and Aaron Courville, 2016.

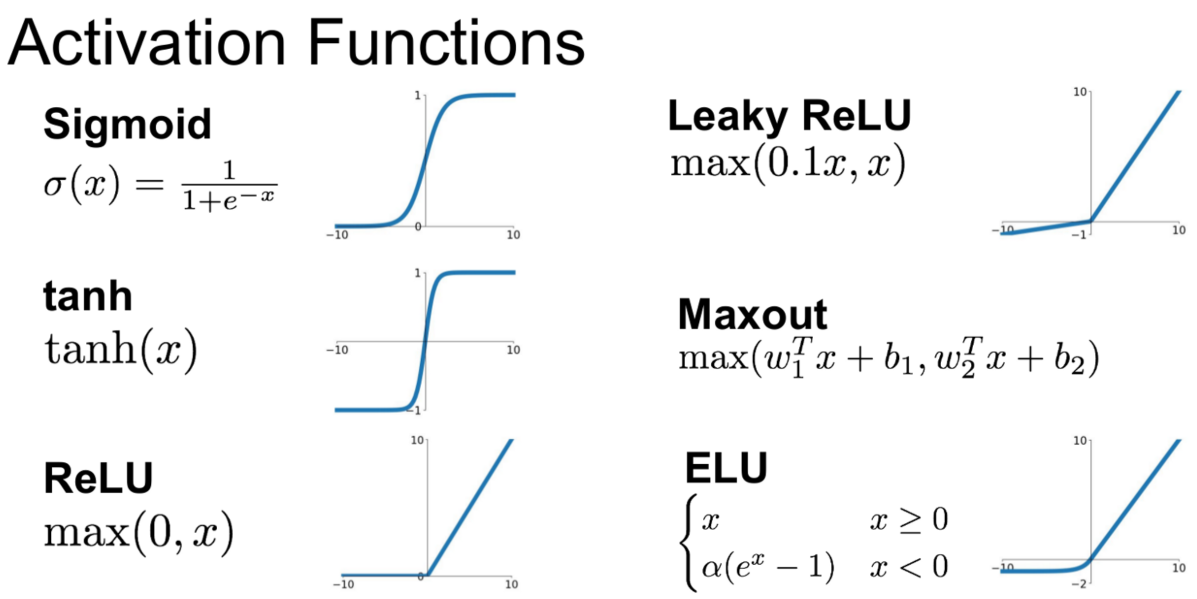
Class Probabilities

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

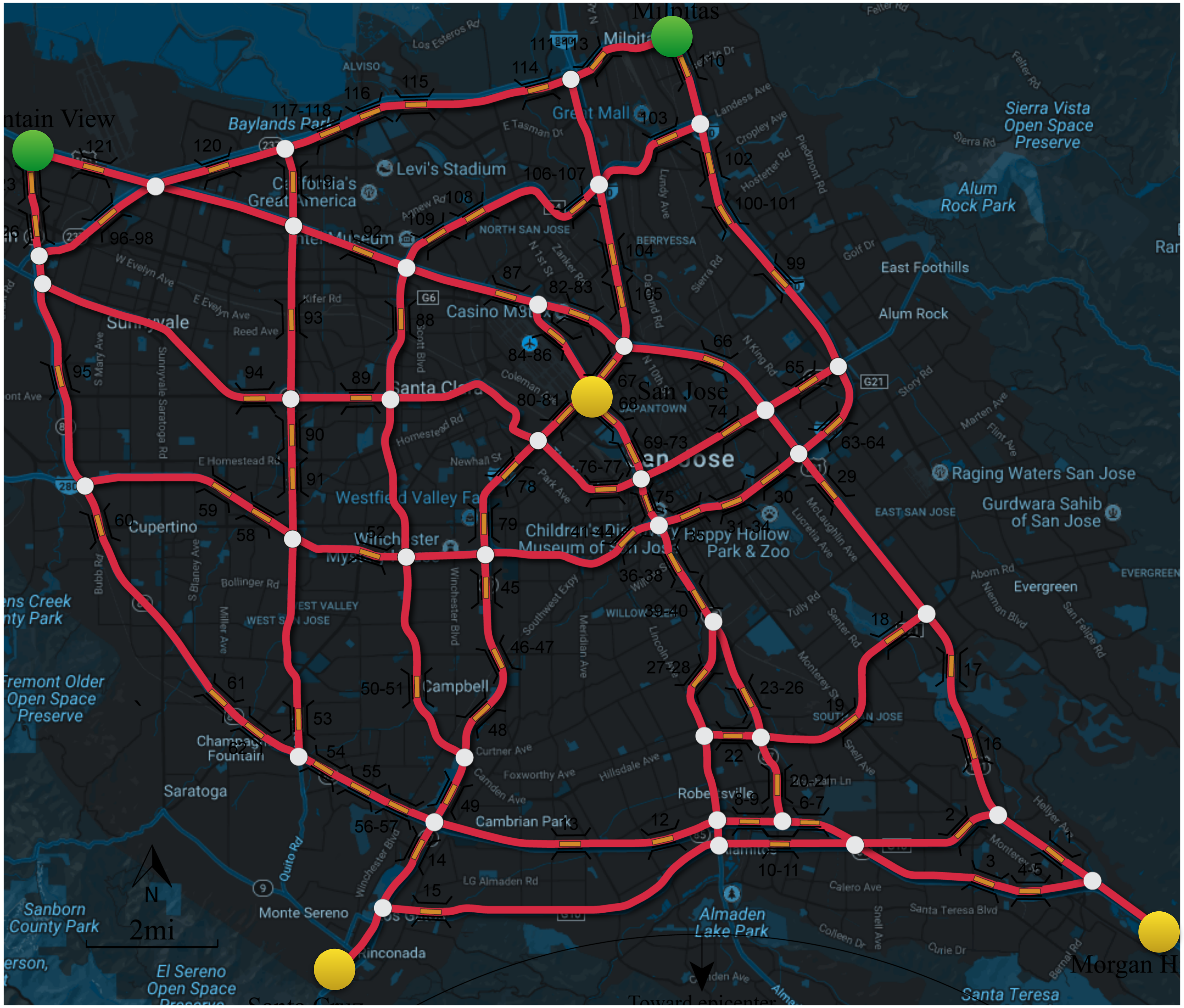
Neurons are trained to filter and detect specific features or patterns by receiving weighted input, transforming it with the activation function and passing it to the outgoing connections.



An example of a neuron showing the input (x_1 - x_n), their corresponding weights (w_1 - w_n), a bias (b) and the activation function f applied to the weighted sum of the inputs.

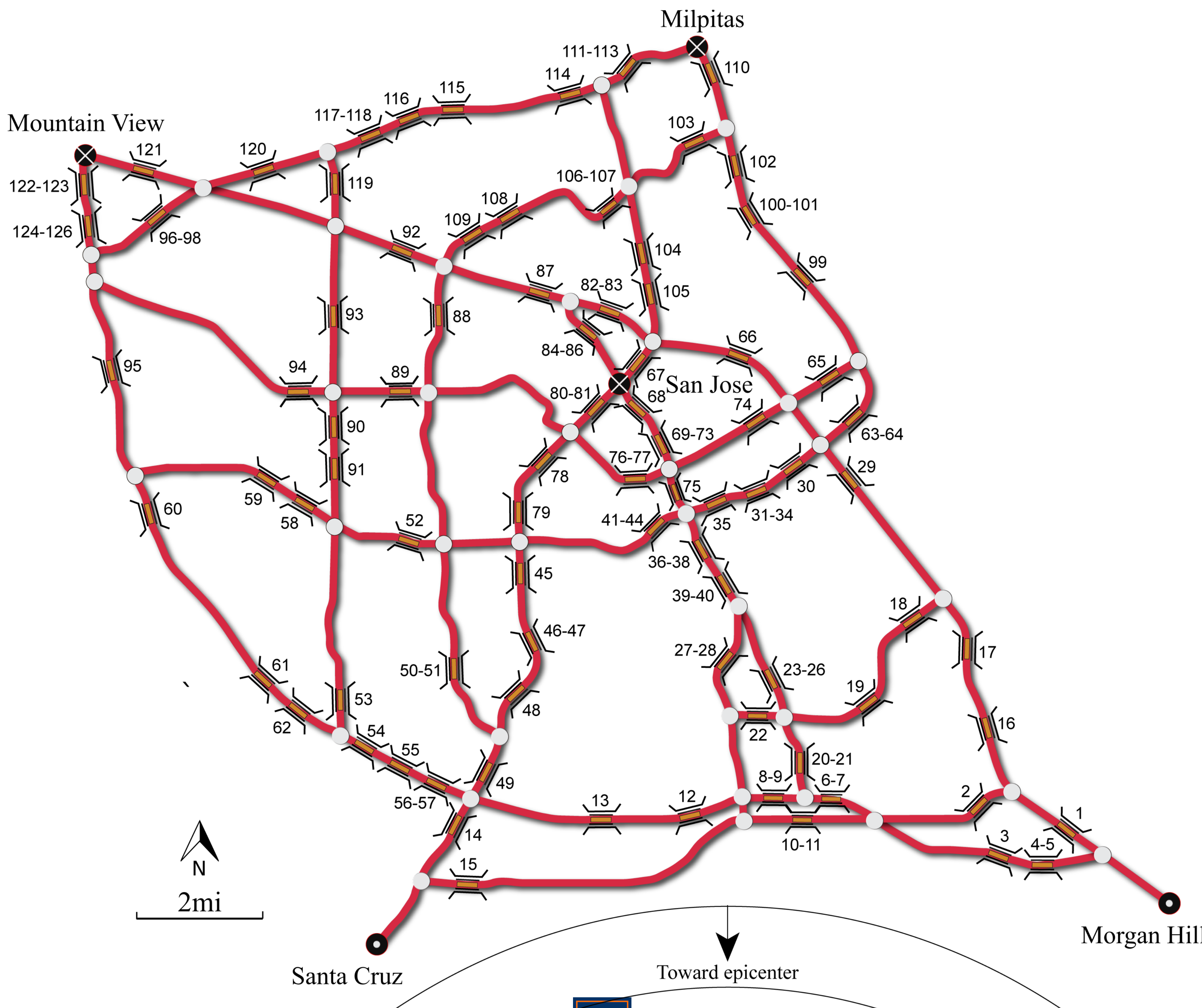


3. CASE STUDY: BAY AREA



Source Node

Terminal Node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San Jose
Santa Cruz
Morgan Hill
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Standard Procedure for k-Terminal Connectivity Evaluation

Find the component-level response of the system subject to an earthquake. The component level response is bridge failure probabilities.

- Involves ground motion intensity prediction and bridge fragility analysis, which are computationally inexpensive [6].

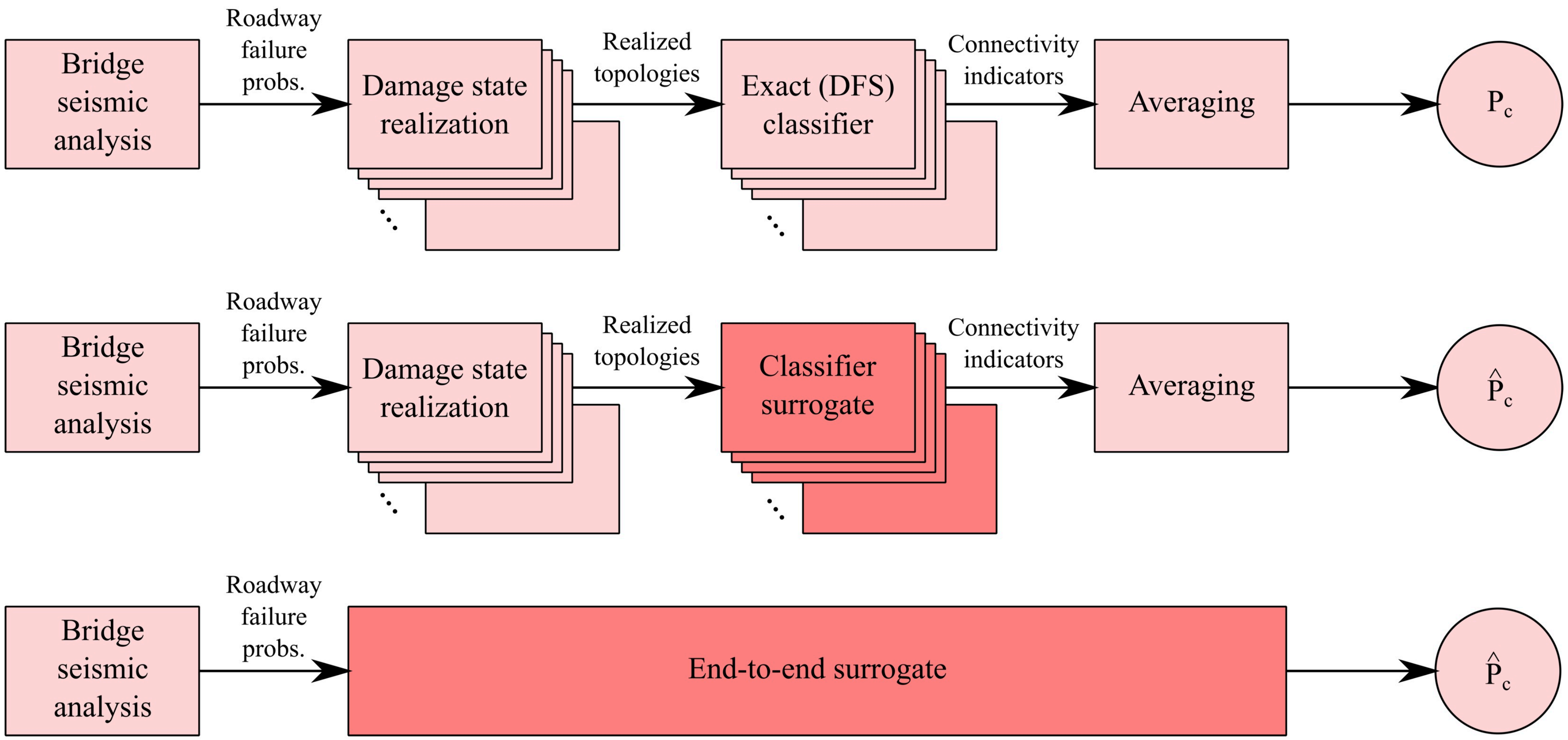
Calculate the system-level response based on the component-level response.

- Computationally expensive.
- Is usually performed using Monte Carlo Simulation.
- In each MCS, a network realization is generated (i.e. bridges will randomly fail or survive), and then the network connectivity is evaluated (i.e. 0 or 1), USING Depth-First Search.
- The process is repeated until convergence is achieved.

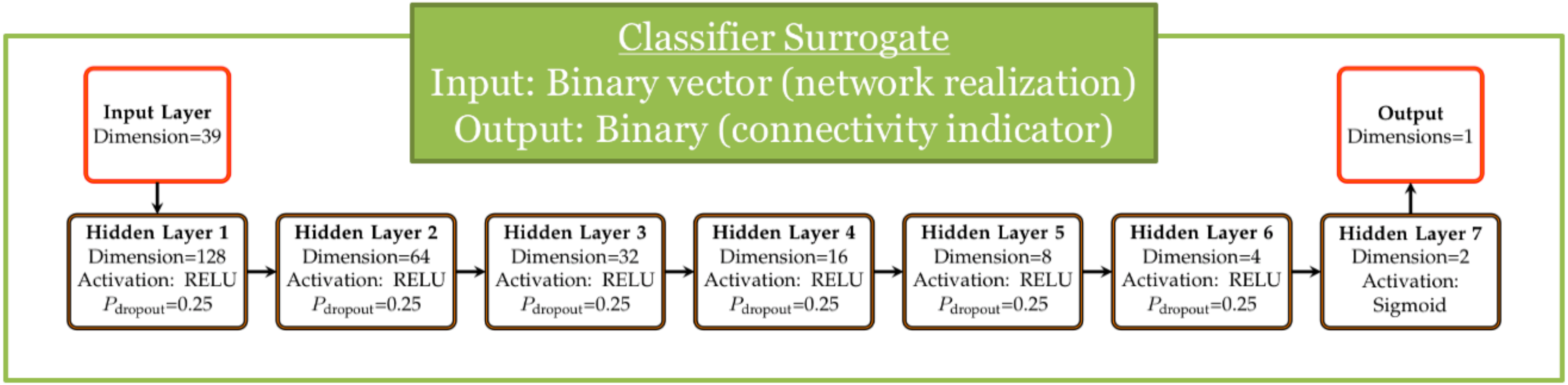
The goal is to accelerate k-terminal reliability analysis using deep neural network surrogates.

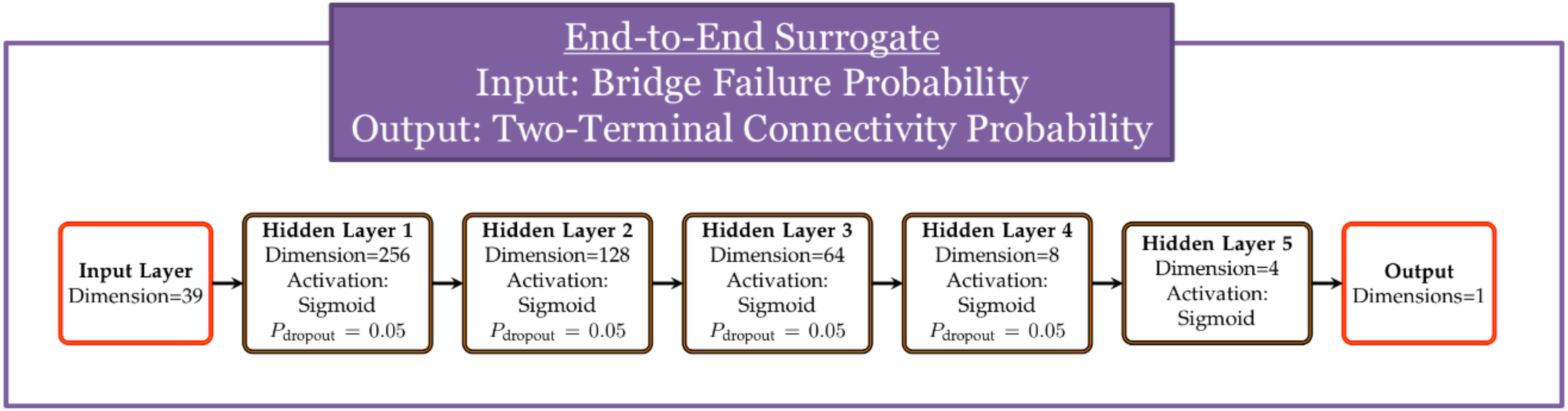
Surrogates are fast models that approximately describe the relationship between the system inputs and outputs and serve as a substitute for more expensive simulation tools.

Workflow for calculation of the expected k-terminal connectivity



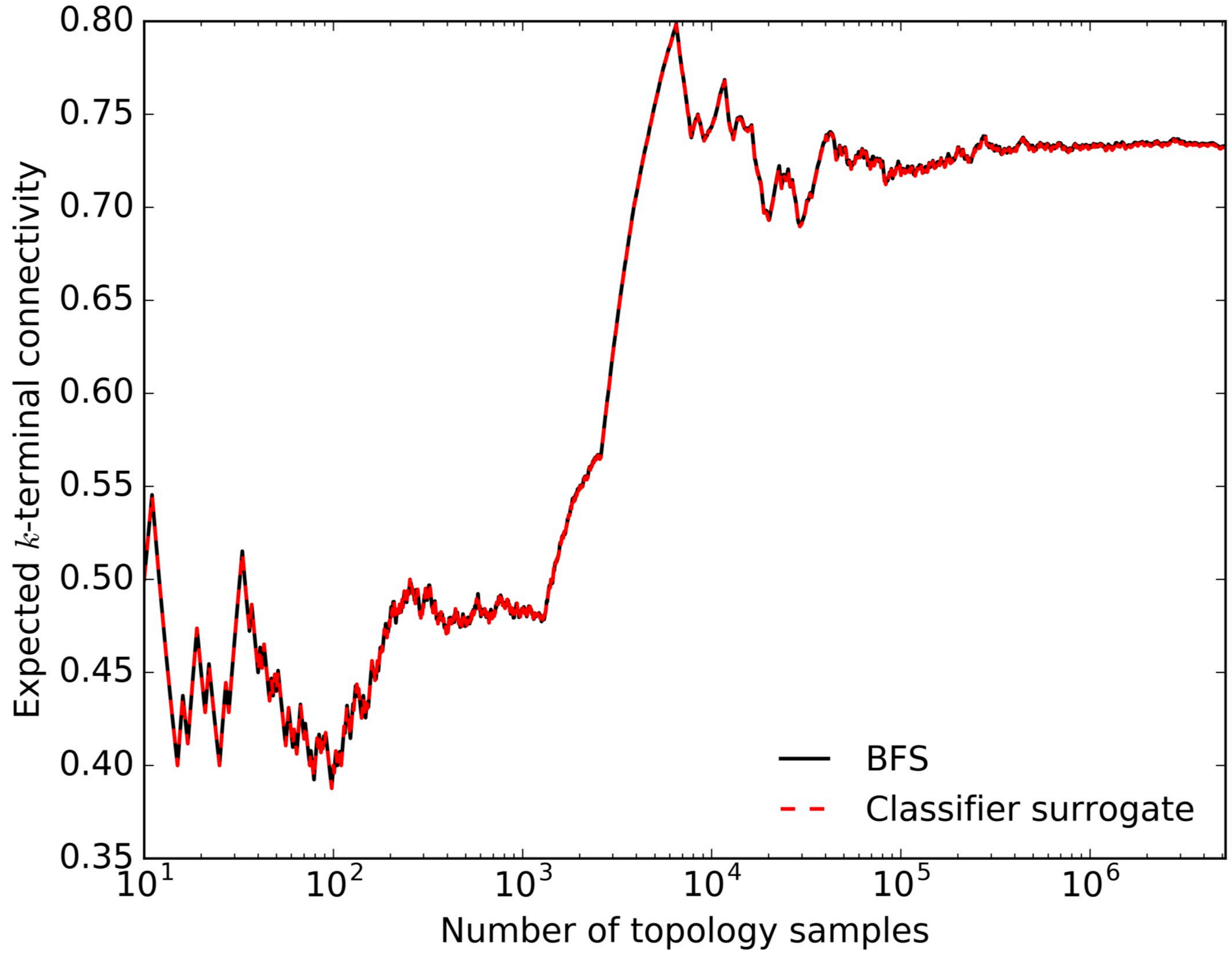
Two types of Surrogates



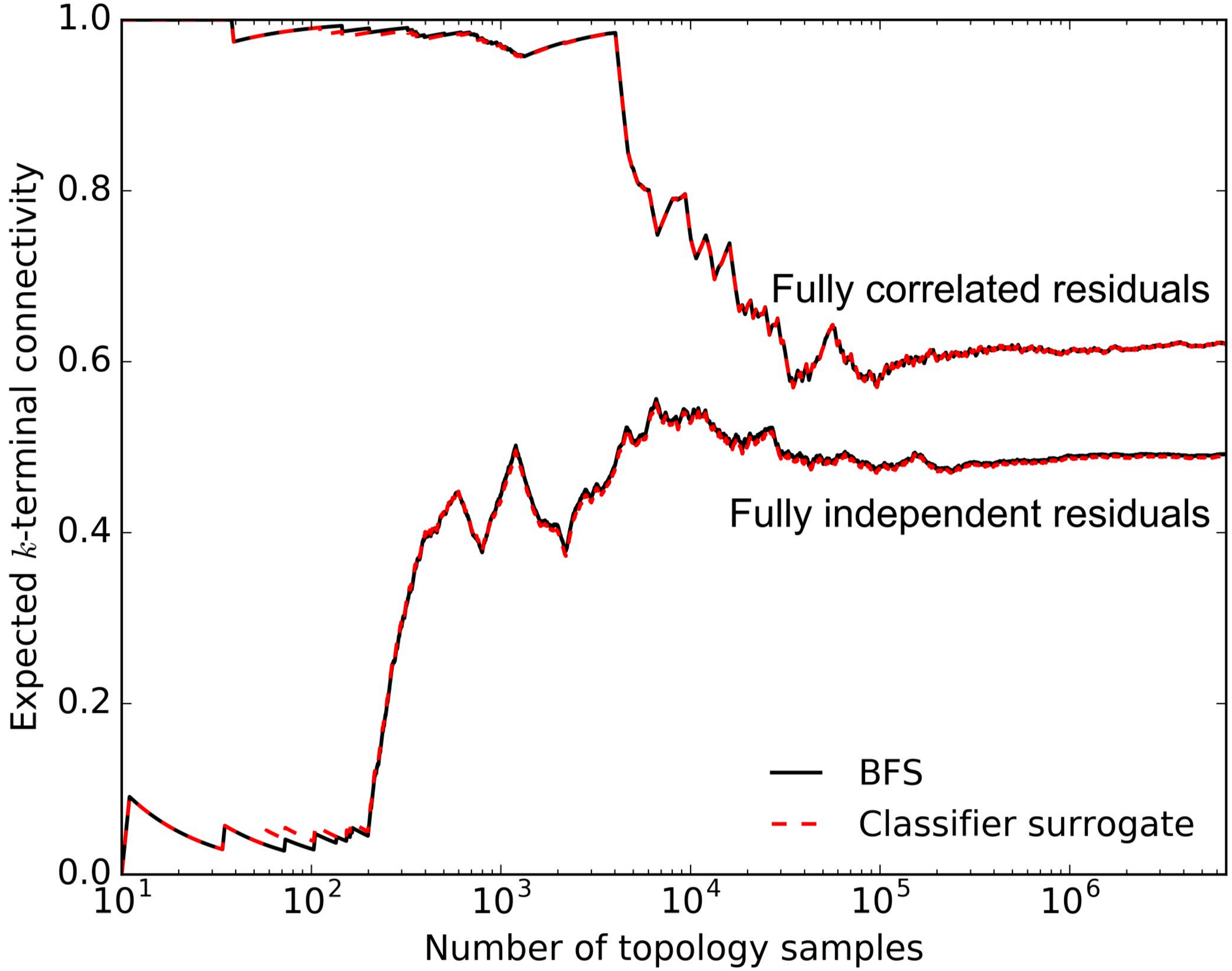


4. RESULTS

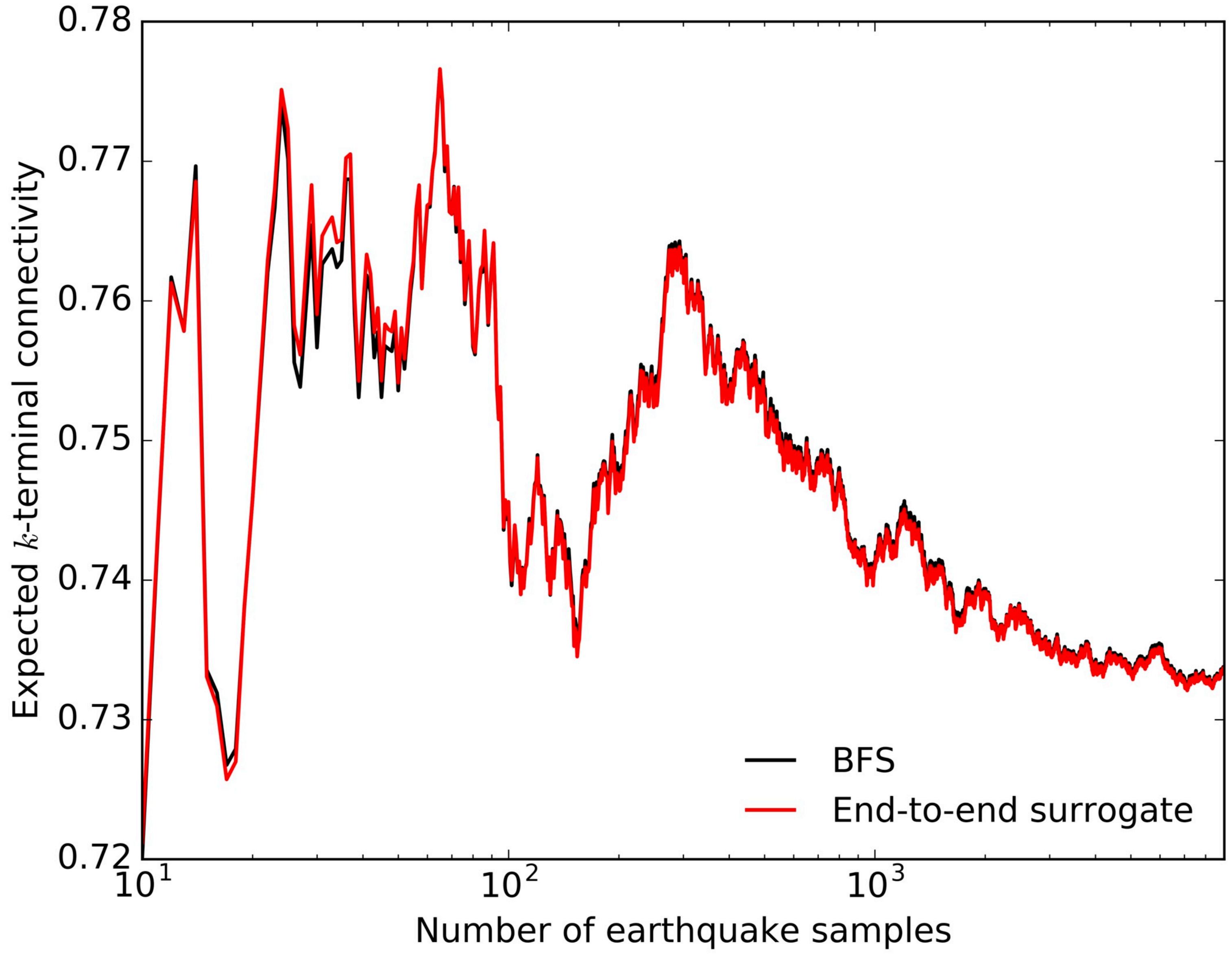
Classifier surrogate results for earthquakes with probabilistic magnitude (ranging between 6.2-7.6 Mw)



Classifier surrogate results for earthquakes with probabilistic magnitude (ranging between 6.2-7.6 Mw) considering the GMPE uncertainties



<u>End-to-end</u> surrogate results for earthquakes with probabilistic magnitude (ranging between 6.2-7.6 Mw)



Computational Time Savings

Surrogate	Execution	Training+Execution
Classifier	20-fold reduction	6-fold reduction
End-to-end	10,000-fold reduction	20-fold reduction

Sensitivity Analysis

Rank	**Roadway with which bridge?**	**Improvement in connectivity (%) (BFS estimate)**	**Improvement in connectivity (%) (DNN estimate)**
1	1	6.07	5.99
2	121	2.91	2.87
3	14	2.10	2.12

Future Work: Sensitivity Analysis

Goal: Quantify the relationship between output (i.e., connectivity) and inputs (i.e., failure probability, network topology).

Challenge: Computation cost is too large/impossible to handle if Monte Carlo Simulation is used.

Methodology: Using gradient of DNN instead of Monte Carlo Simulation to alleviate computational burden.

Applications:
-- Test robustness of system in the presence of uncertainty.
-- Identify critical system components for upgrading/investment.

References

[1] Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning*. MIT Press.
[2] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553):436– 444.
[3] Hossein Hashemi, Khaled Abdelghany, Sepide Lotfi. "End-to-End Deep Learning Framework for Real-Time Traffic Network Management" Accepted for publication in Transportation Research Record and Presentation in Transportation Research Board 97th Annual Meeting.
[4] Isola, Phillip, Jun-Yan Zhu, Tinghui Zhou, and Alexei A. Efros. "Image-to-image translation with conditional adversarial networks." *arXiv preprint arXiv:1611.07004* (2016).
[5] Ledig, Christian, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken et al. "Photo-realistic single image super-resolution using a generative adversarial network." *arXiv preprint arXiv:1609.04802* (2016).

Thank you!