UNIVERSITY OF ILLINOIS
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Deep Learning for Accelerating Infrastructure System Reliability Analysis

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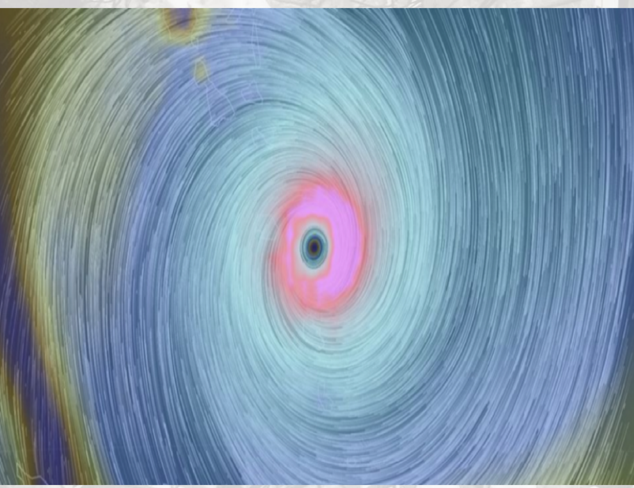

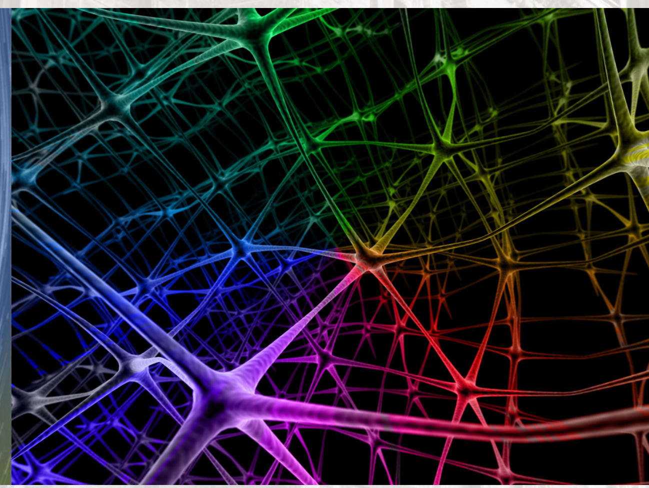

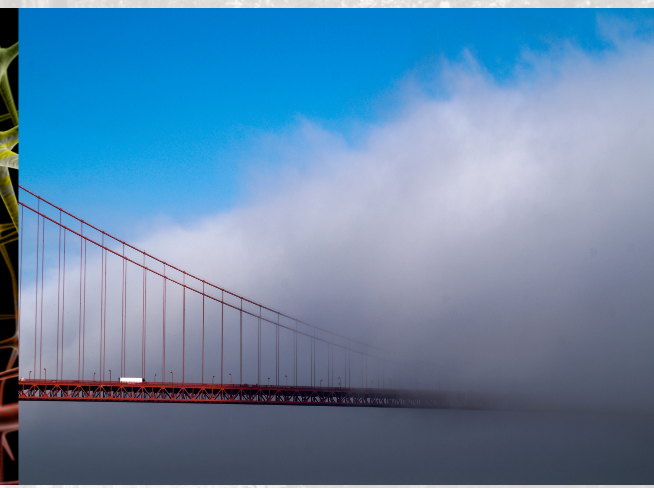

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- Part II: Deep Learning for Accelerating Infrastructure System Reliability Analysis

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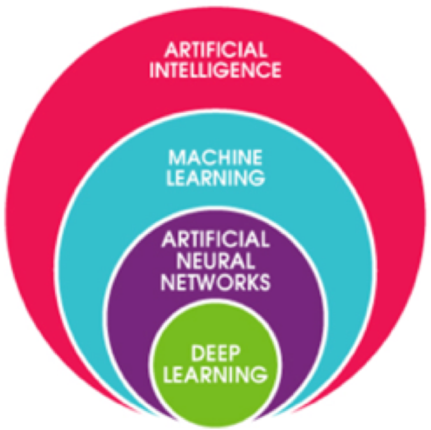
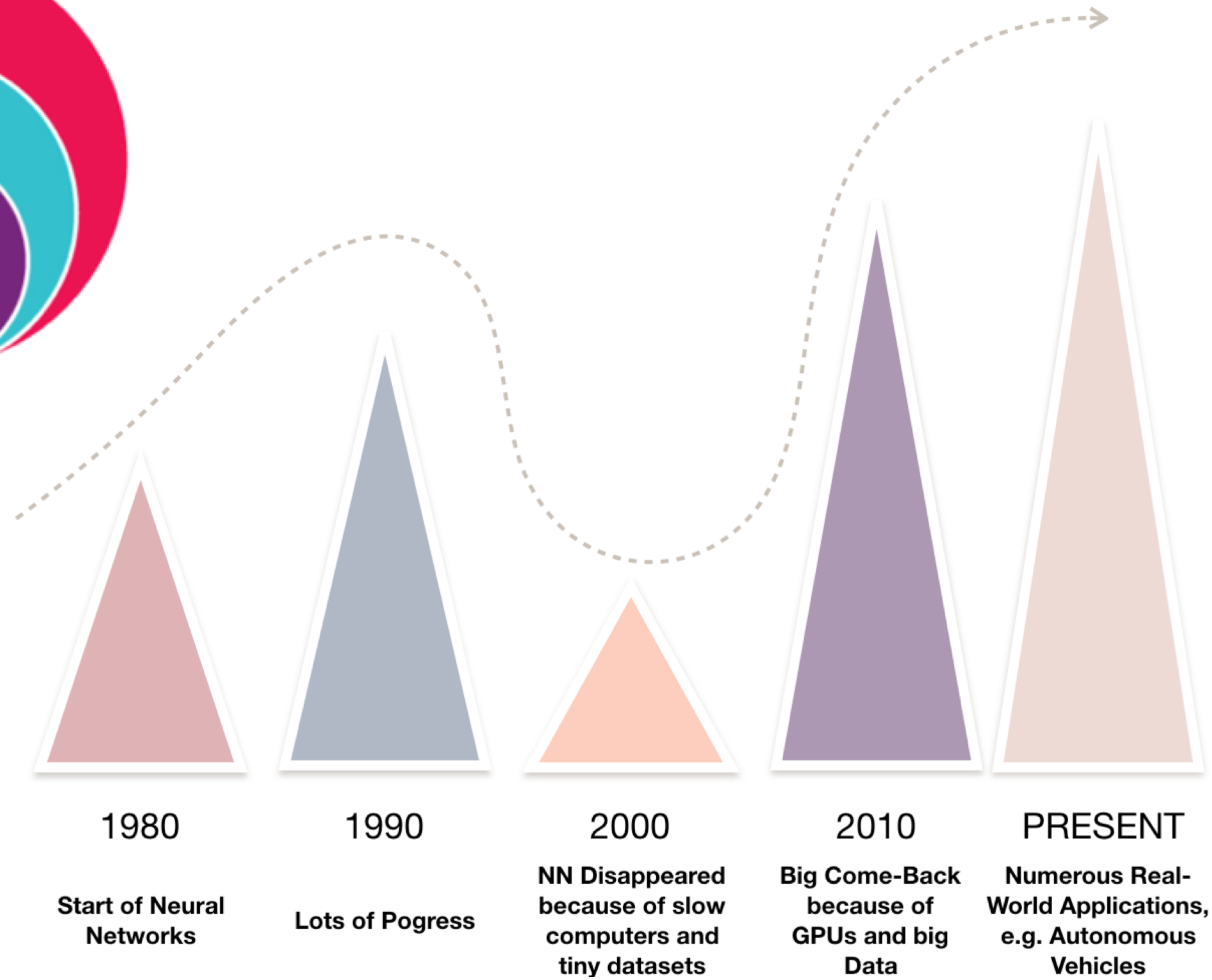
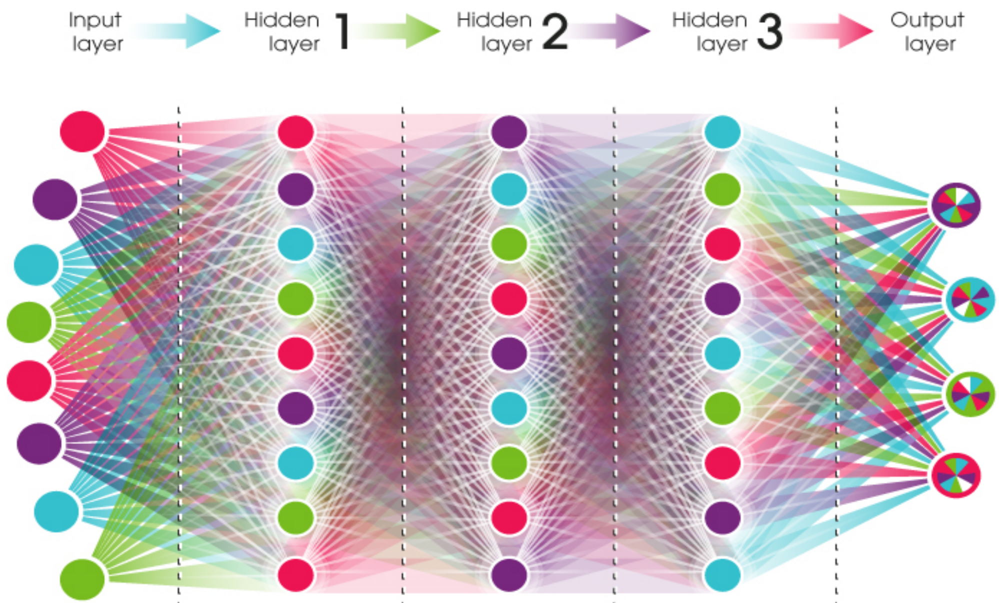
History


ARTIFICIAL INTELLIGENCE
MACHINE LEARNING
ARTIFICIAL NEURAL NETWORKS
DEEP LEARNING

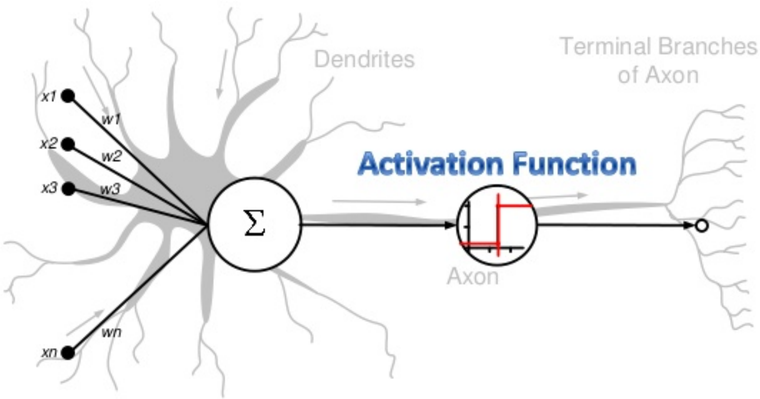

1980
Start of Neural Networks
1990
Lots of Pogress
2000
NN Disappeared because of slow computers and tiny datasets
2010
Big Come-Back because of GPUs and big Data
PRESENT
Numerous Real-World Applications, e.g. Autonomous Vehicles

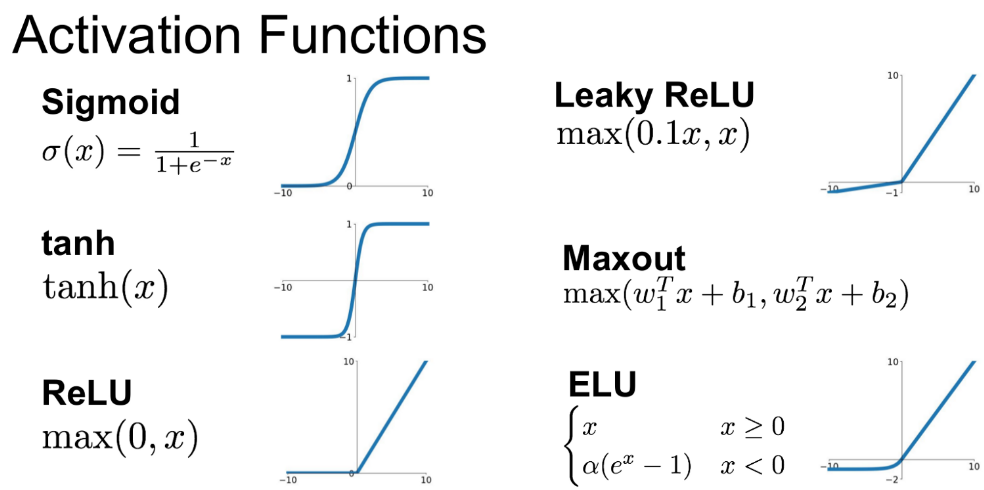
What is a Deep Neural Network?



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

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 [1,2].



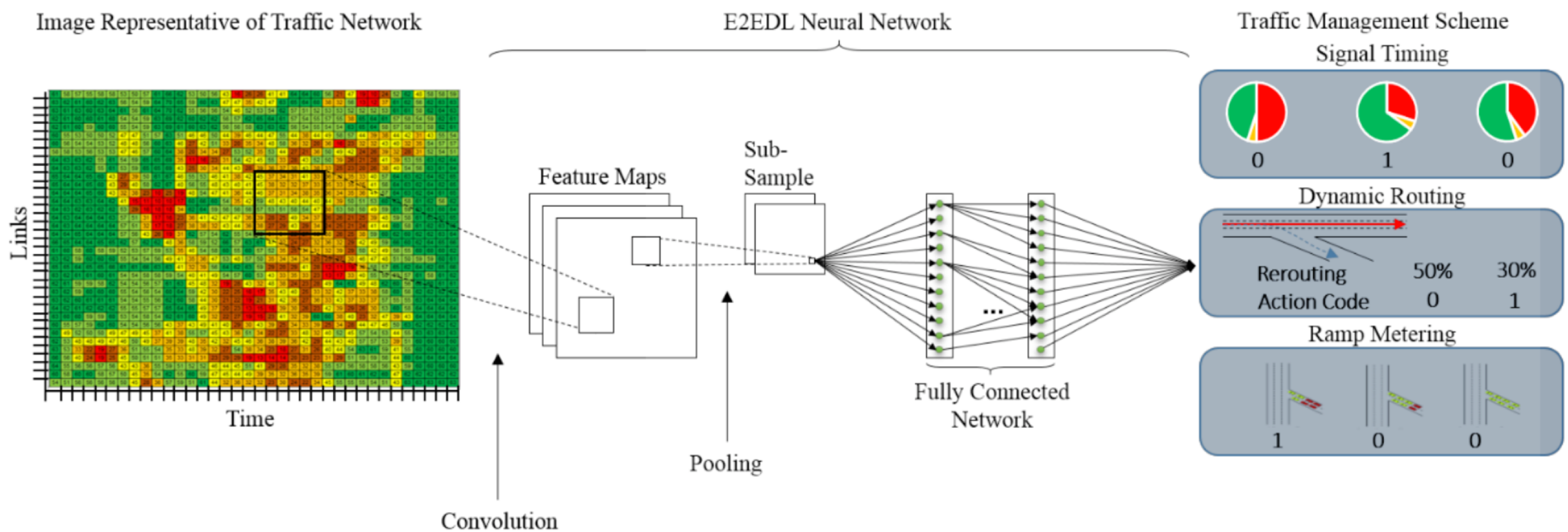


credit : Andrew L. Nelson

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.

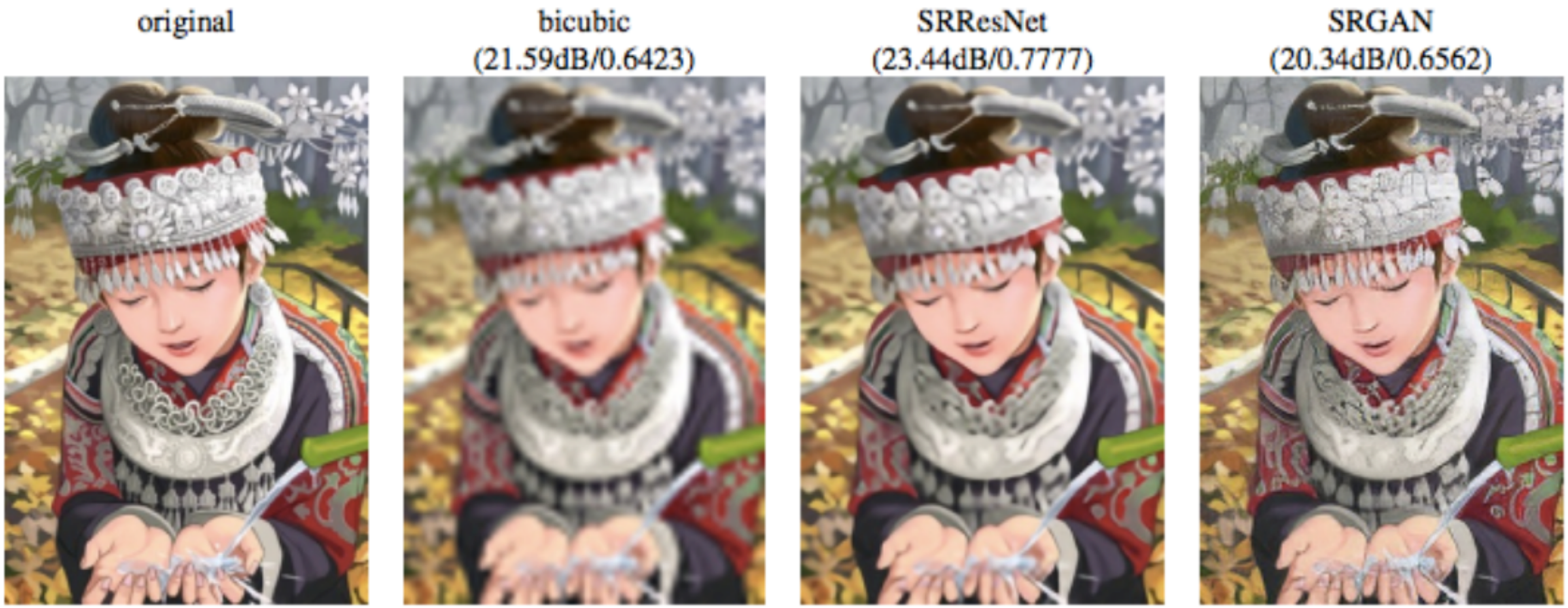
End-to-End Deep Learning Framework for Real-Time Traffic Network Management [3]



E2EDL Input	E2EDL System	E2EDL Output

Image-to-image translation with conditional adversarial networks [4]

Photo-realistic single image super-resolution using a generative adversarial network [5]



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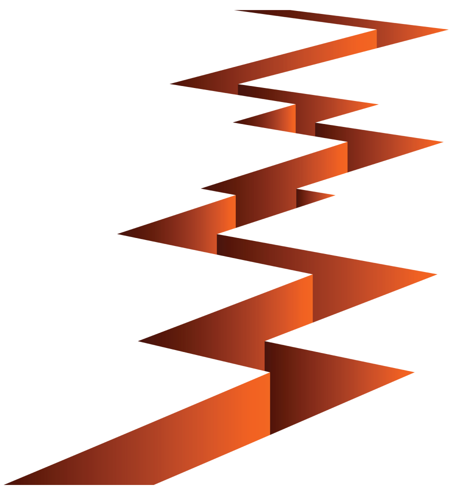
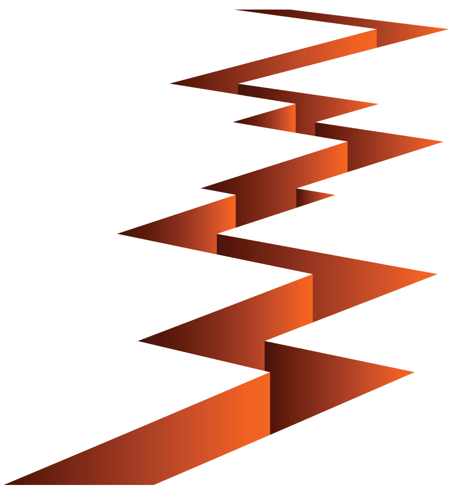
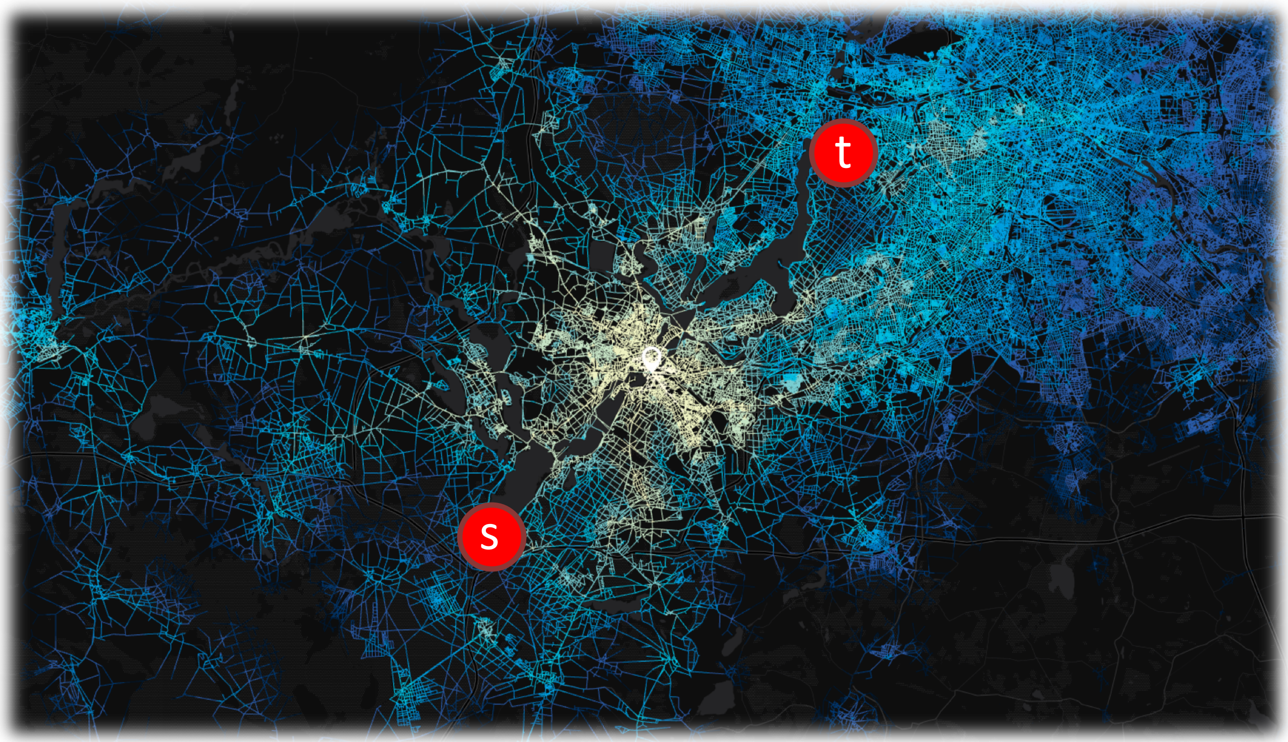
Problem Statement



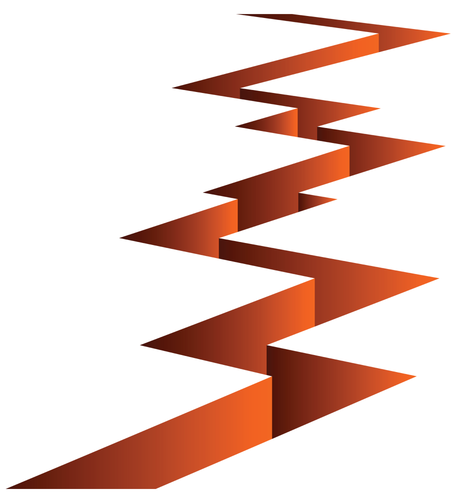
Two-terminal Reliability





Quantity of interest: Probability that nodes s and t are connected after the given earthquake.

Why is this important?



The 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.

Standard Procedure for Two-Terminal Connectivity Evaluation

1. 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].

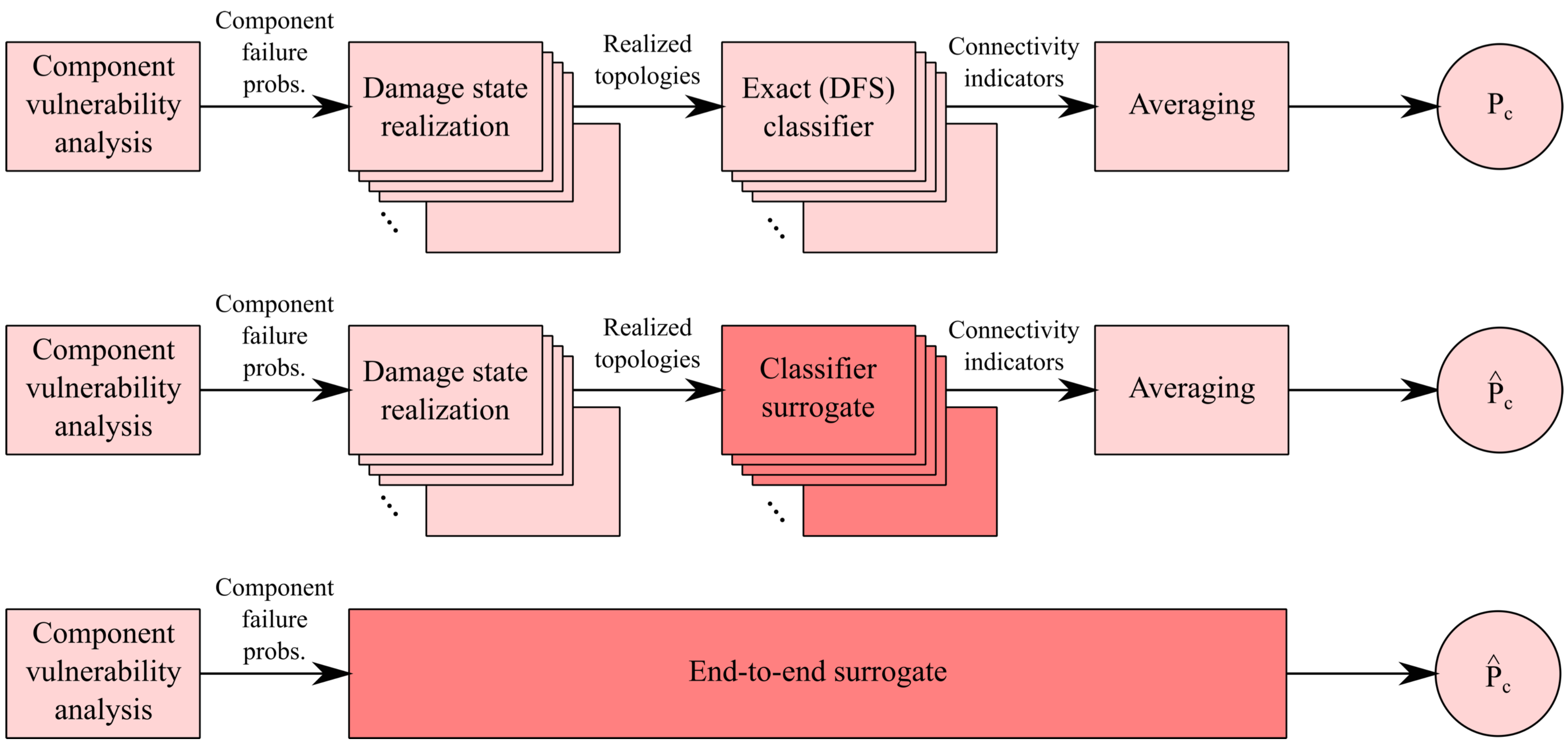
2. Calculate the system-level response based on the component-level response.
   - Computationally expensive.
   - Is usually performed using Monte Carlo Simulation.
   - In each MCS, a network realization is generated (i.e. bridges will randomly fail or survive), and then the network connectivity is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

Expensive!

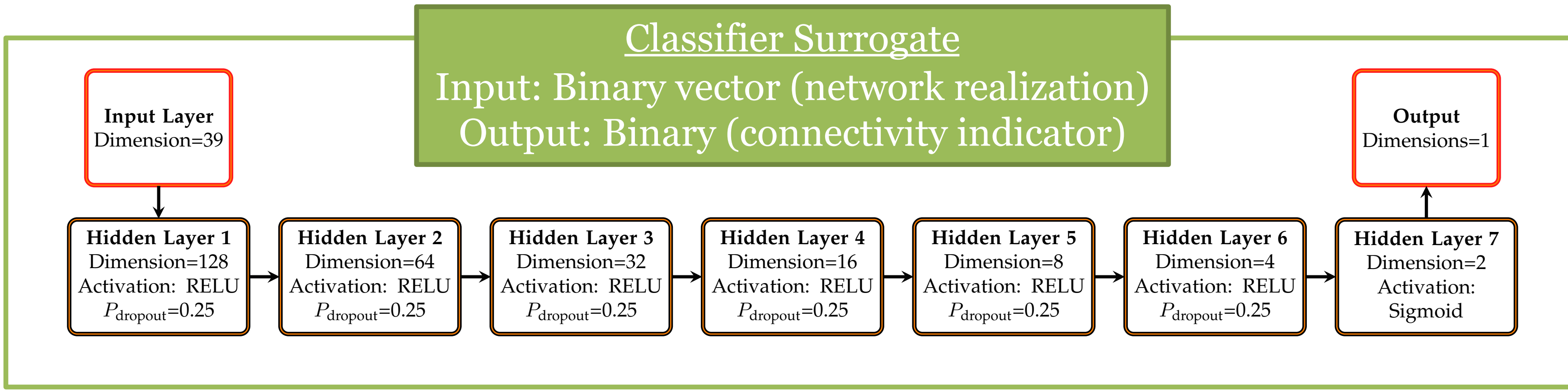
What is a surrogate?

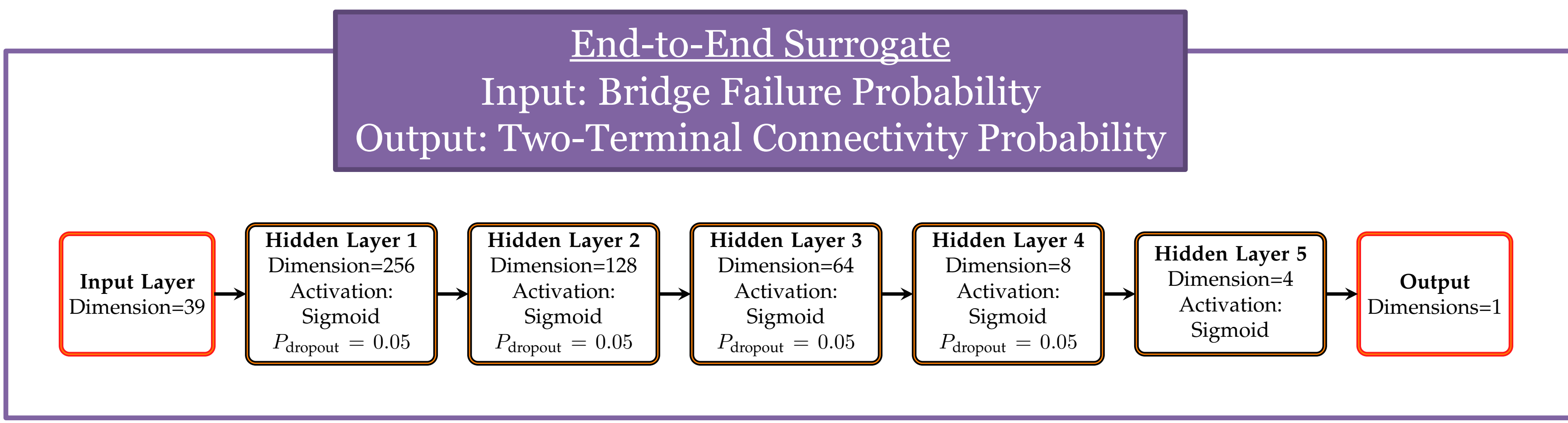
Surrogates are fast models that approximately describe the relationship between the system inputs and outputs and serve as a substitute for more expensive simulation tools.

Workflow for calculation of the expected two-terminal connectivity

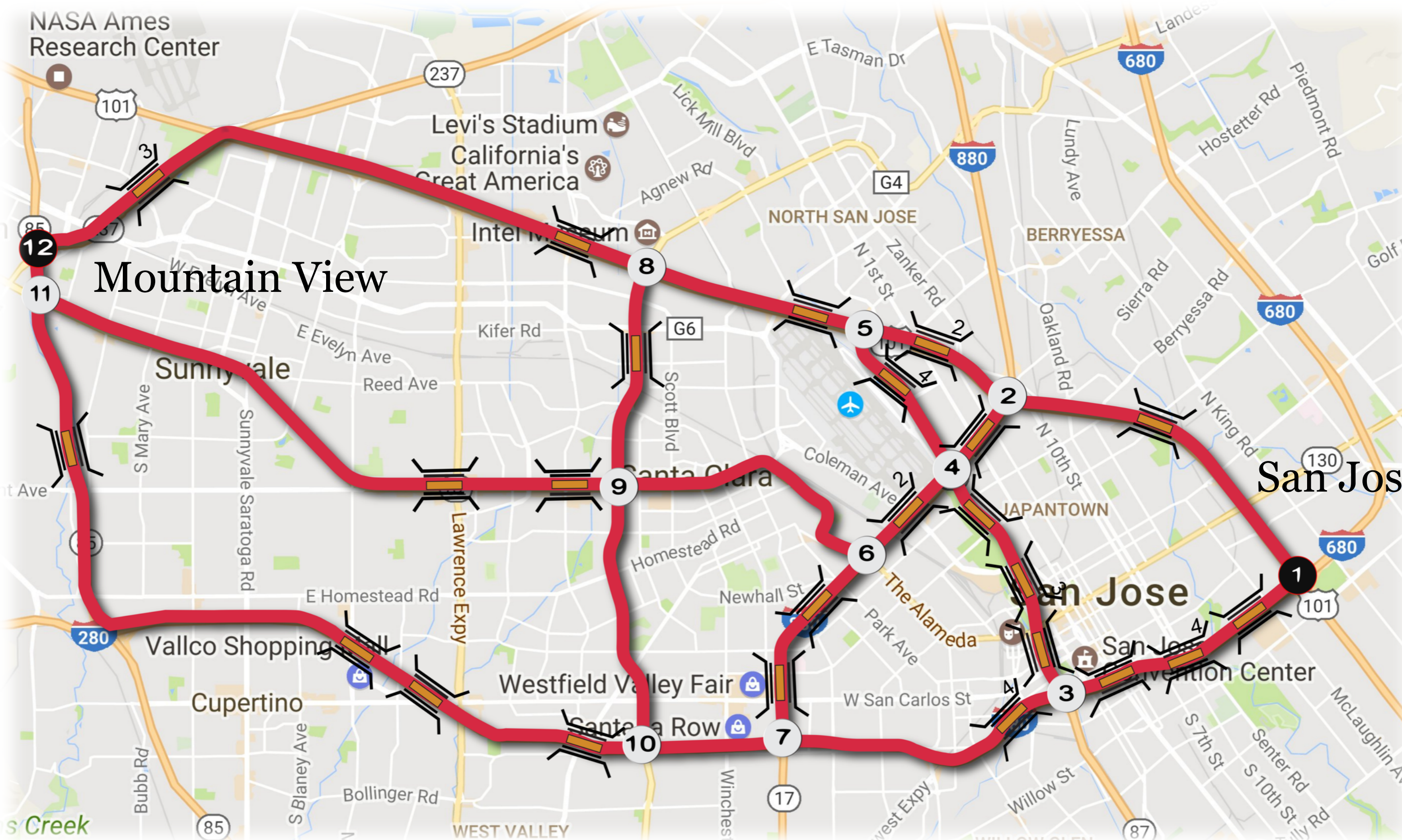


Two Types of Surrogates

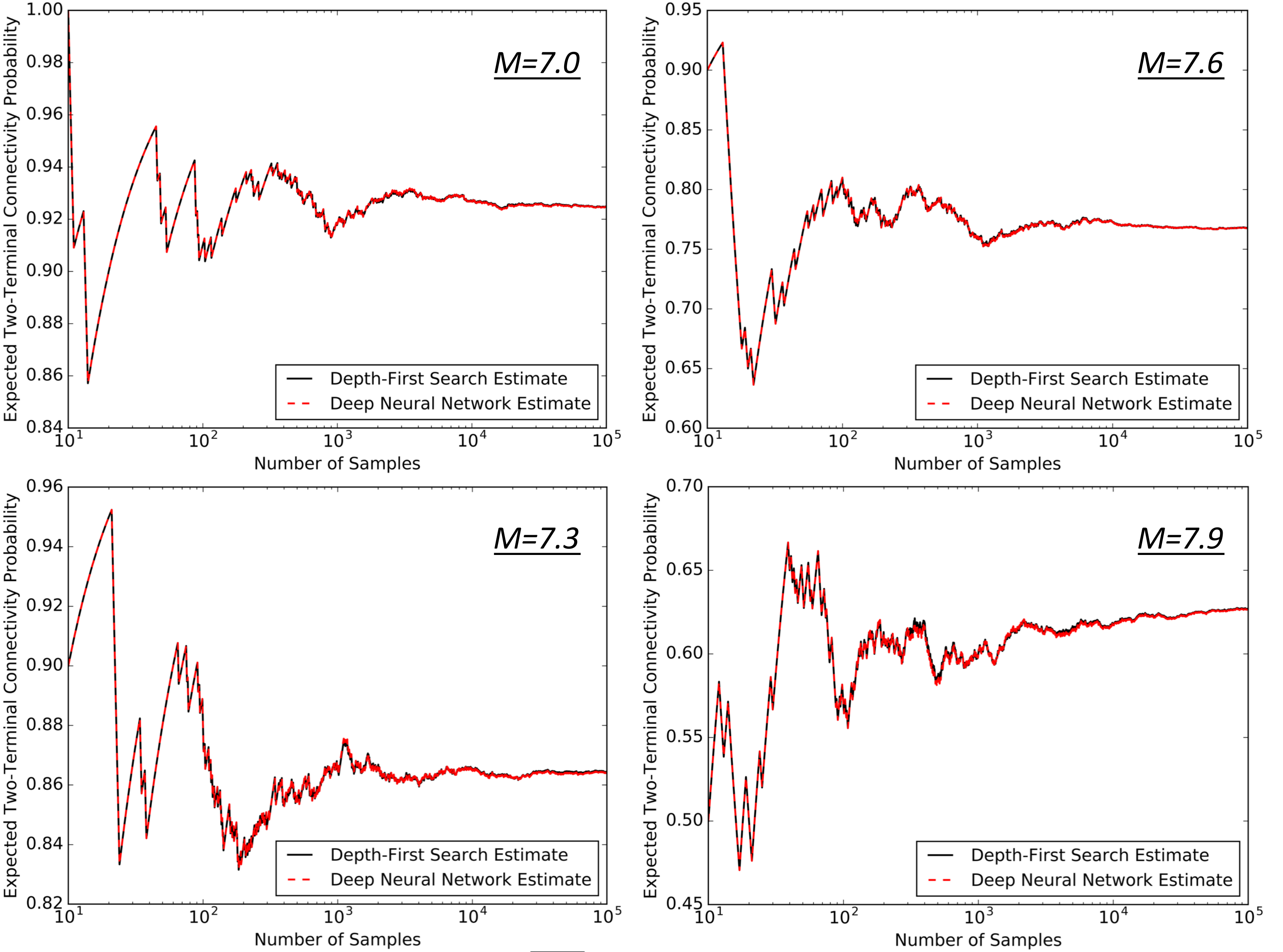




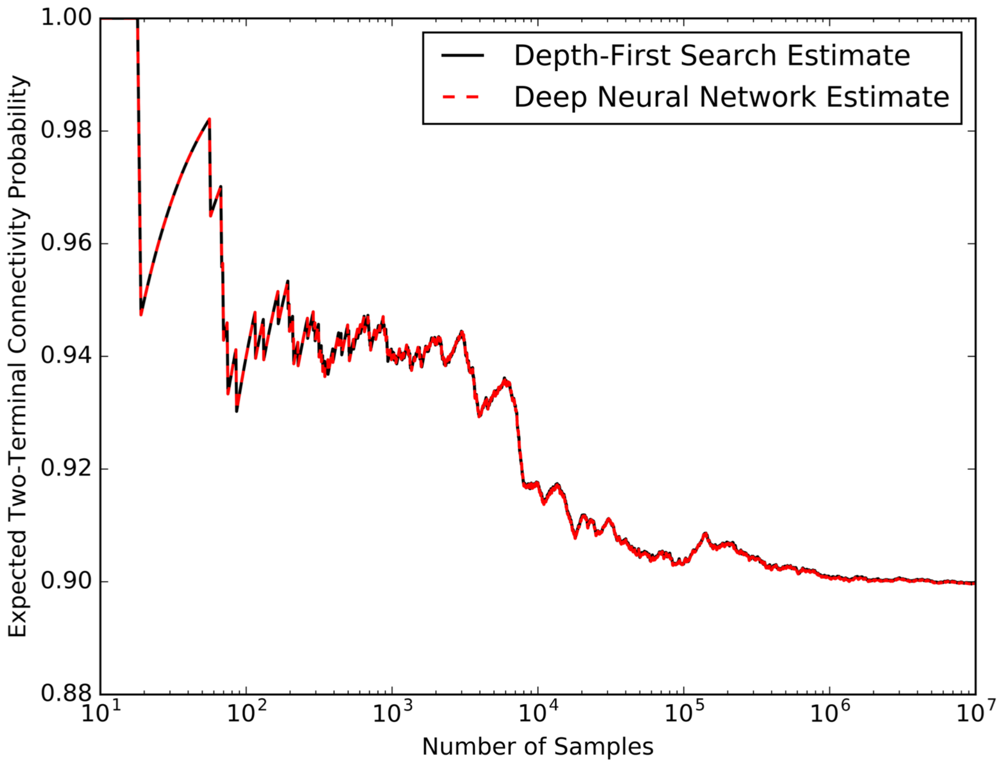
The network connecting San Jose to Mountain View



Classifier surrogate results for earthquakes with deterministic magnitude



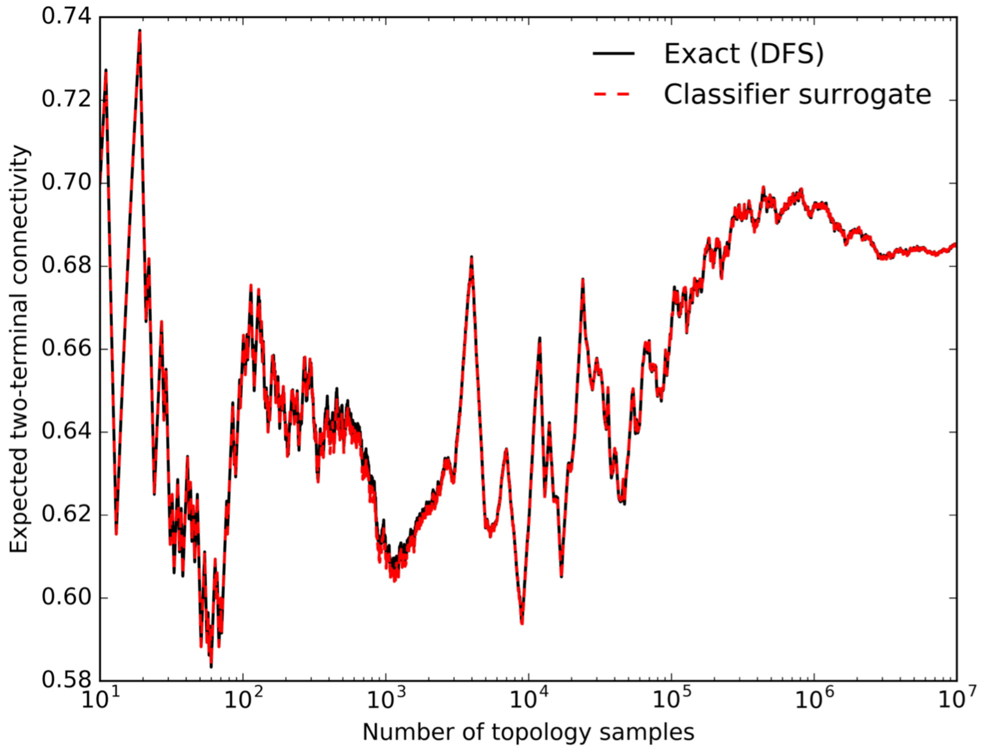
<u>Classifier</u> surrogate results for earthquakes with probabilistic magnitude (ranging between 6.9-7.4 Mw)



Standard Computational time: 647.83 s

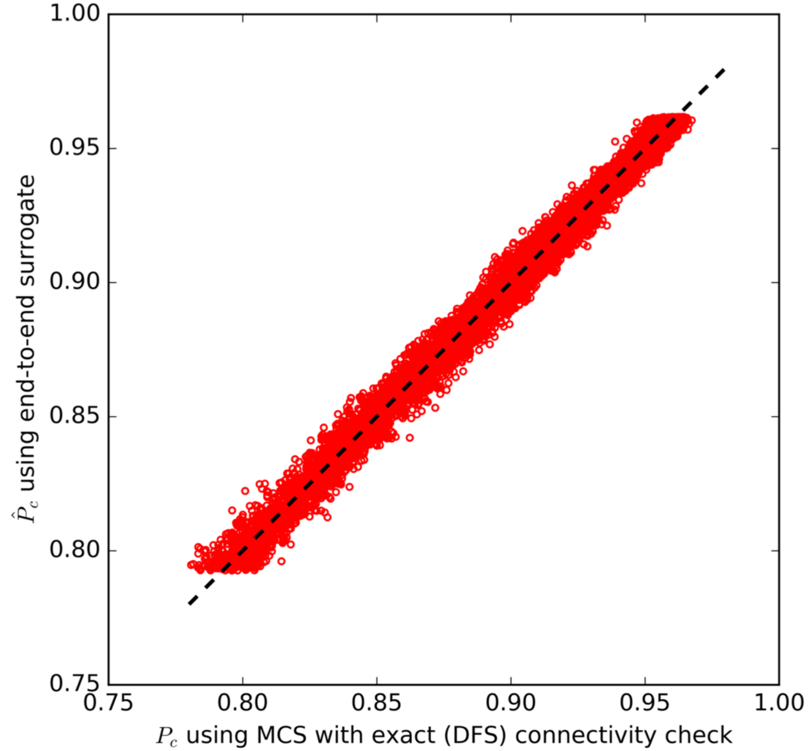
Surrogate computational time: 98.33 s

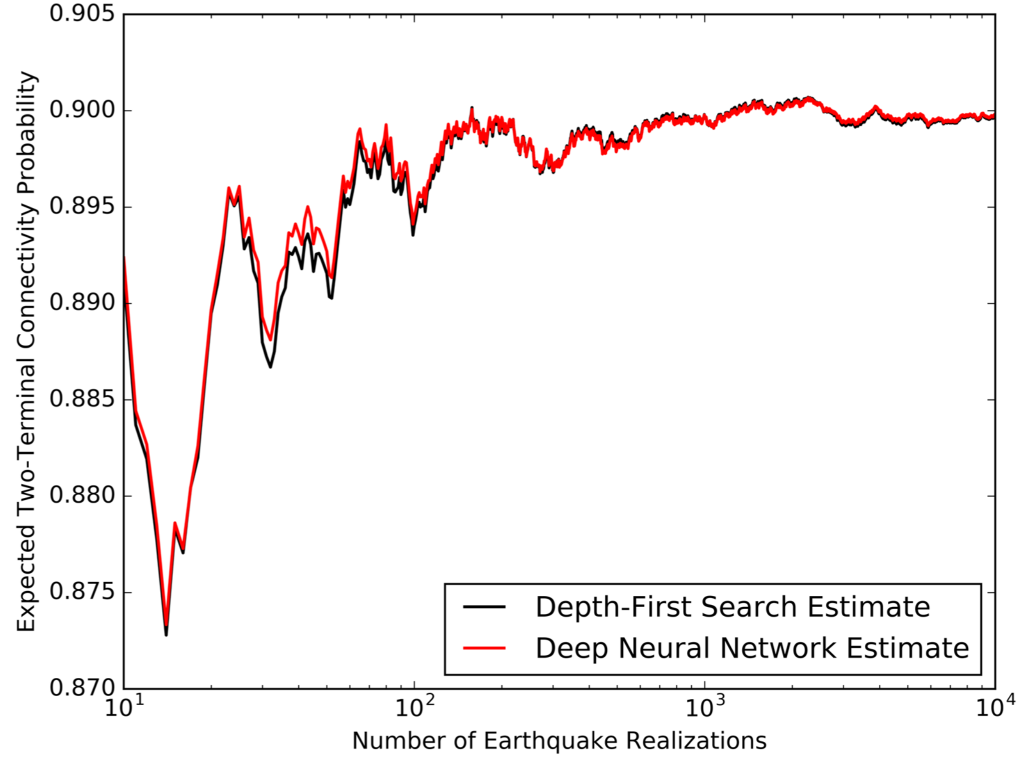
Classifier surrogate results for earthquakes with probabilistic magnitude (ranging between 6.9-7.4 Mw) considering the GMPE uncertainties



Standard Computational time: 647.83 s
Surrogate computational time: 98.33 s

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





Standard Computational time: 7882.74 s
Surrogate computational time: 0.71 s

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!