Bayesian Framework for Performance Assessment and Risk Management of Transportation Systems Subject to Earthquakes

PEER Transportation Systems Research Program

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WHAT IS THE OBJECTIVE?

The objective is to develop a Bayesian network (BN)-based framework for seismic infrastructure risk assessment/management and decision-support to aid:

- Pre-event decisions (e.g. identification of critical components, prioritization of retrofit/mitigation)
- Immediate post-event decisions (e.g. dispatch of emergency personnel and inspectors)
- Longer-term post-event decisions (e.g. prioritization of reconstruction efforts)

WHAT IS A BN?

A BN is a probabilistic graphical model representing random variables (nodes) and their dependencies (links)

WHAT ARE THE CHALLENGES?

- BNs can be computationally demanding/intractable for complex systems with dependent components
- Methods must be developed to construct the BN models in optimal/efficient formulations
- Approximation methods must be developed to balance accuracy and computational demands

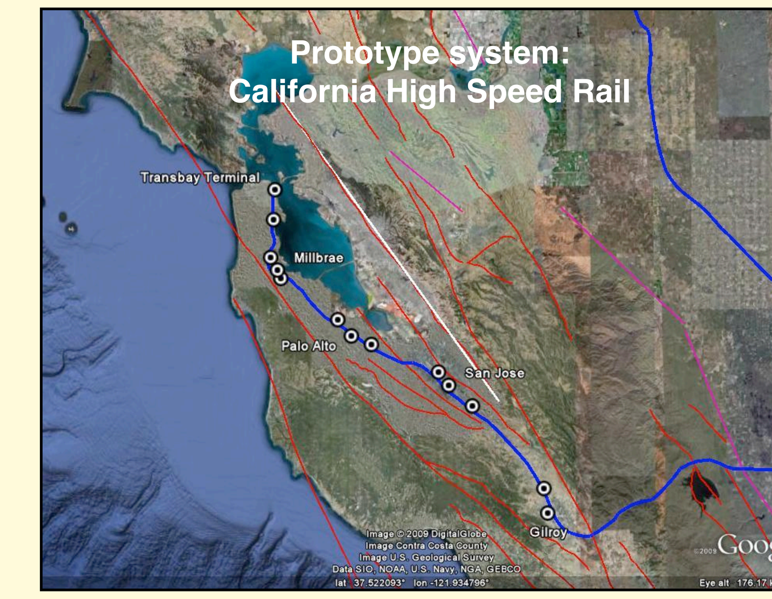
WHY USE BNS?

BNs:

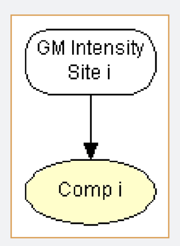
- Are graphical & intuitive (tool for end-users)
- Can account for sources of uncertainty
- Can be probabilistically updated in near-real time
- Can model multiple hazards and interdependencies
- Can model distributed and interacting systems
- Can be used to identify critical components/cutsets
- Can be extended by utility & decision nodes to solve decision problems

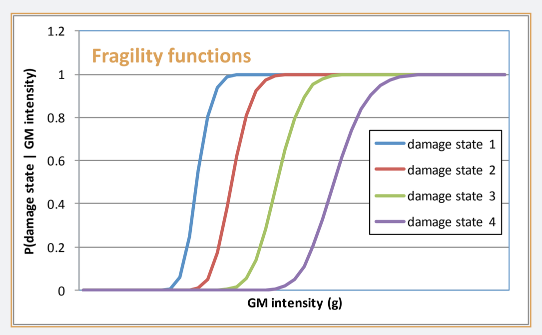
WHAT ARE THE PROPOSED APPLICATIONS?

- The general framework has been developed to aid risk assessment/management and decision support for general lifelines systems (e.g. transportation networks, pipelines, electrical distribution systems)
- The framework is currently being applied to the proposed California High Speed Rail system to act as a prototype for future applications



COMPONENT PERFORMANCE MODELS





The performance of components in an infrastructure system can be modeled using fragility functions. Fragility functions define the conditional probability of exceeding the k^{th} damage state (DS) given a ground motion intensity (GMI) :

P(exceeding DS k|GMI).

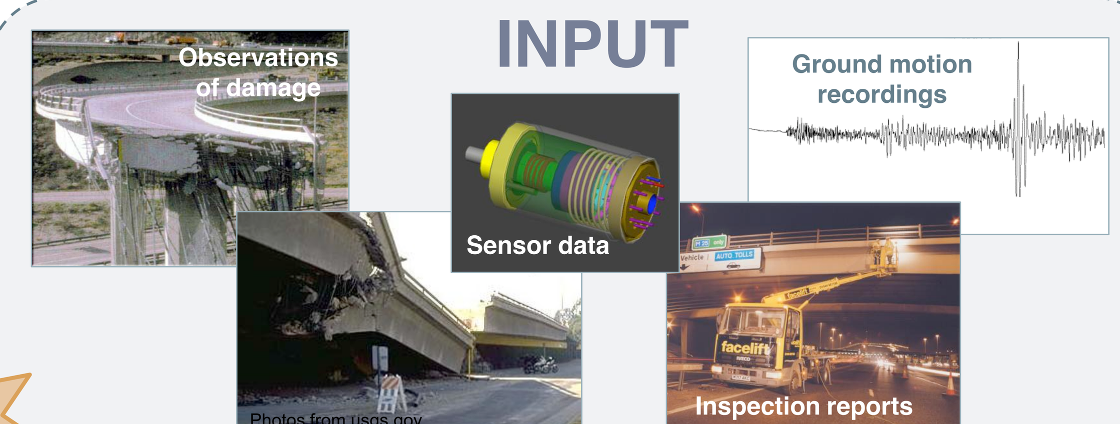
The conditional probability of a component being in the k^{th} DS can then be defined:

P(component in DS k|GMI) =

P(exceeding DS k|GMI) - P(exceeding DS k+1| GMI)

where k=0 implies the intact component damage state.

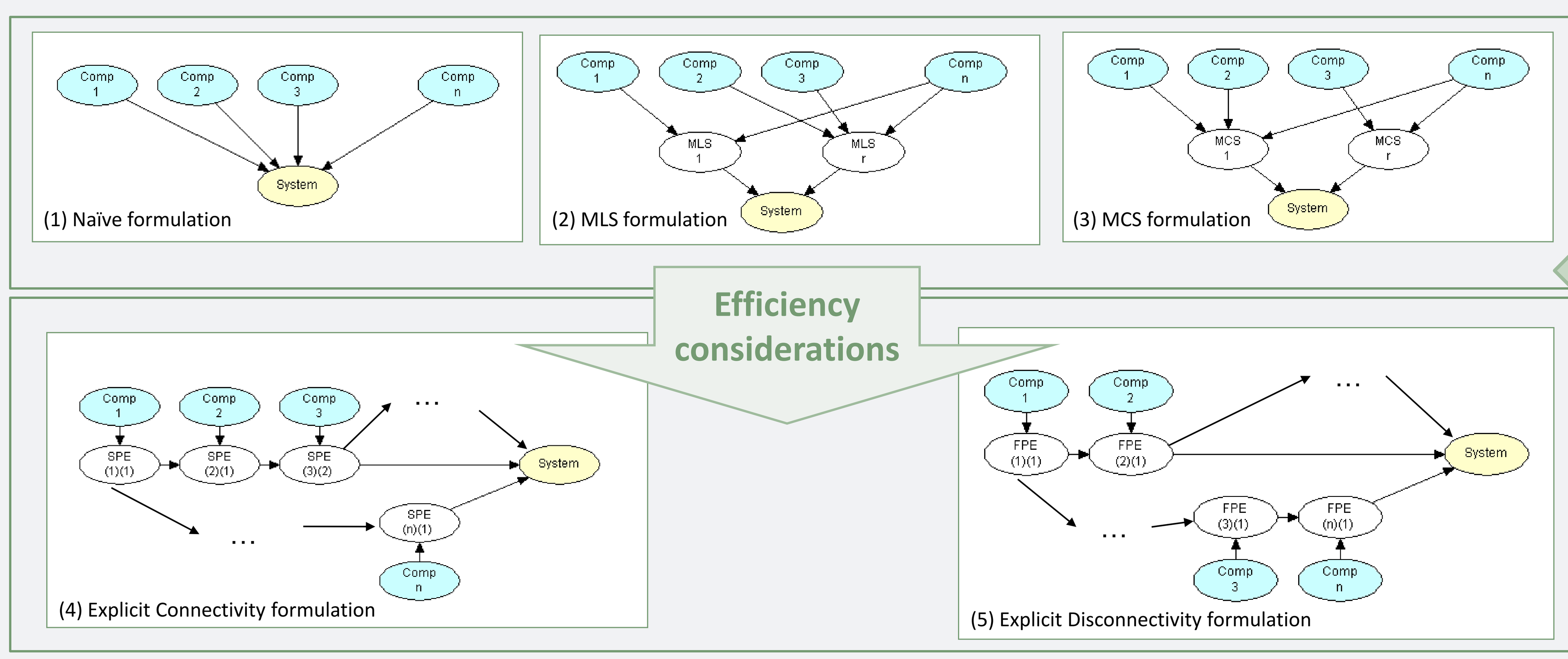
INPUT



Incoming information propagates through the BN to probabilistically update modules.

BAYESIAN NETWORK SERVES AS A FRAMEWORK FOR PROCESSING PROBABILISTIC INFORMATION BETWEEN MULTI-DISCIPLINARY MODULES

EFFICIENT SYSTEMS ANALYSIS FORMULATIONS



Five formulations have been developed for modeling system performance using BNs. Three of the formulations were developed based on classical systems analysis techniques:

(1) The *Naïve formulation* links all nodes directly into the system node requiring the consideration of all combinations of component states. This quickly renders the BN intractable even for small systems.

(2) The *Minimum Link Set (MLS) formulation* requires the enumeration of all MLSs, each of which is represented by a node. Links connect components to the MLSs of which they are a part. For binary-state components (BCs), a MLS node is in survival state only if all its components are in survival state. The state of the system is a function of the MLS nodes and, for BCs, the system is in survival state if any MLS node is in survival state.

(3) The *Minimum Cut Set (MCS) formulation* is the dual of the MLS formulation (i.e. the MCS formulation uses the MCSs instead of MLSs and the functional relationships are defined oppositely).

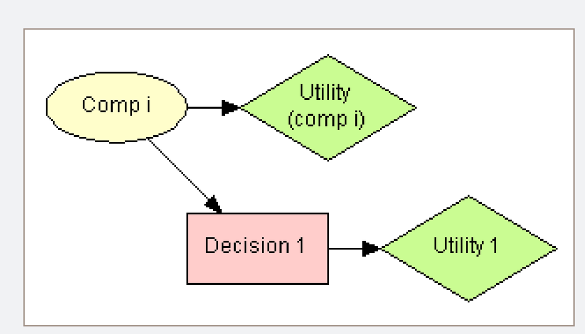
These three classical formulations are not sufficiently efficient for modeling system performance within the context of BNs and can result in exponentially increasing computational demands. To address this, the classical-analysis-based formulations are adapted to produce more efficient explicit formulations:

(4) The *Explicit Connectivity (EC) formulation* arranges sequences of events known as survival path sequences (SPSs) which are comprised of "survival path events" (SPEs). SPEs are functions of their corresponding components and the preceding survival path events in the sequence. The SPSs can be constructed manually for small systems, but require use of MLSs for complex systems.

(5) The *Explicit Disconnectivity (EDC) formulation* is the dual of the EC formulation. It is a pessimistic approach, creating "failure path sequences" made of "failure path events."

The explicit formulations arrange nodes into chain-like structures instead of the converging structure used in the classical formulations. It has been seen, in general, that such formulations are more efficient within the context of BNs. To automate the construction of the explicit formulations, a heuristically augmented binary integer optimization program is in the later-stages of development.

DECISION SUPPORT MODELS



BNs can be extended to include decision nodes (rectangles) and utility nodes (diamonds) to create an influence diagram. Links from chance nodes (ovals) to decision nodes indicate information that is known prior to making a decision. Utility nodes specify a consequence/benefit as a function of a particular outcome of a chance node or decision.

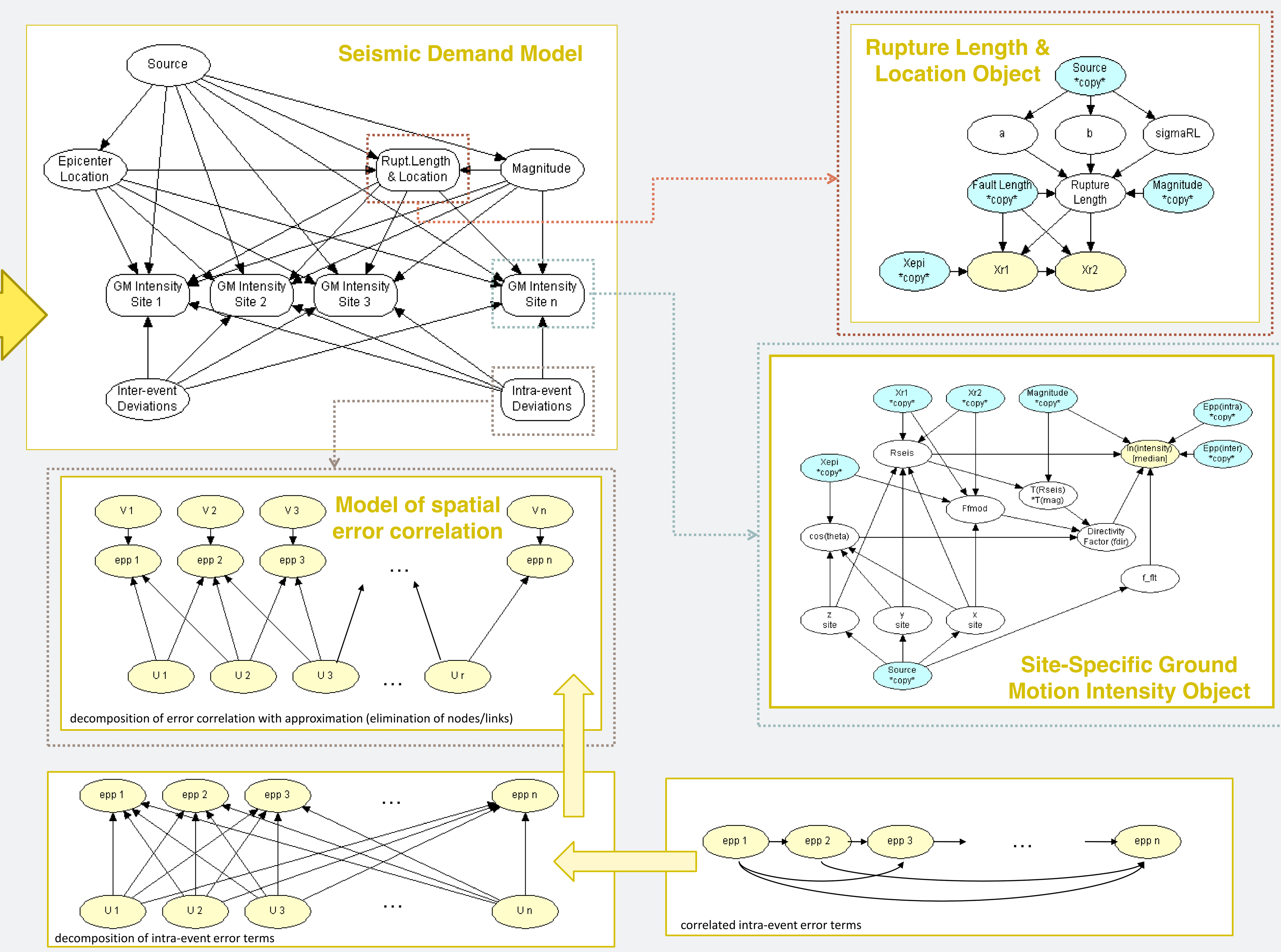
A decision support model is currently under development to aid post-earthquake inspection prioritization.

GROUND MOTION INTENSITY MODELED AS SPATIALLY DISTRIBUTED RANDOM FIELD

The seismic demand model provides distributions of ground motion (GM) intensity at different sites across an infrastructure system by modeling GM intensity as a spatially distributed random field:

$$\ln(S_i) = \ln(\overline{S_i}) + f_{dir} + \epsilon_m + \epsilon_{r,i}$$

GM prediction equations can be used to compute the median GM intensity ($\overline{S_i}$) at each site as a function of source and site characteristics. The seismic demand model accounts for uncertainty in finite rupture length, uncertainty in GM prediction equations (ϵ_m,$\epsilon_{r,i}$), as well as incorporating directivity effects (f_{dir}). The Seismic Demand Model BN utilizes objects, represented by rectangles with rounded corners, behind which are hidden additional BNs. There are three different objects in this seismic demand BN shown below: (1) rupture length and location object, (2) intra-event error object, and (3) site-specific GM prediction object. The seismic demand model is capable of considering multiple sources by using source-specific local coordinate systems.



The intra-event errors terms are in fact spatially correlated (a structure that is computationally inefficient to model using BN). Thus, a transformation of the form **ε** = **TU**+**SV** is sought (where **T** is a transformation matrix, **S** is a diagonal matrix, and **U**,**V** are vectors of statistically independent standard normal random variables). The terms of the transformation matrix can be interpreted as factors on the links between U-nodes and ε-nodes. Because sparsely connected BNs are more efficient (and densely connected BNs can be intractable), it is necessary to eliminate as many links between U-nodes and ε-nodes as possible (i.e. terms of the transformation matrix are set to zero). An investigation into the modeling of random fields via BN has suggested a numerical optimization scheme for determination of the transformation matrix and elimination of a large number of links without significant loss of accuracy.

This project was made possible with support from:

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