# How Current BNs Fail to Represent Evolvable Pattern Recognition Problems and a Proposed Solution

Nirmalya Ghosh, and Bir Bhanu

*Center for Research in Intelligent Systems (CRIS), Univ. of California, Riverside, USA 92521*

nirmalya@ee.ucr.edu, bhanu@ee.ucr.edu

## Abstract

*In the real world, systems/processes often evolve without fixed and predictable dynamic models. To represent such applications we need uncertainty models, like Bayesian Nets (BN) that are formed online and in a self-evolving data-driven way. But current BN frameworks cannot handle simultaneous scalability in the model structure and causal relations. We show how current BNs fail in different applications from several fields, ranging from computer vision to database retrieval to medical diagnostics. We propose a novel Structure Modifiable Adaptive Reason-building Temporal Bayesian Networks (SmartBN) that has scalability for uncertainty in both, structures and causal relations. We evaluate its performance for a 3D model building application for vehicles in traffic video.*

## 1. Introduction

For systematic handling of uncertainty in systems or processes, probabilistic model like Bayesian Net (BN) [1] is used. The causal structure may be hand coded by experts [3] or learned from data with example systems [9], *but remains the same at all time*. But systems often dynamically change in **one or more** of the following. **(a)** Different sets of active variables (e.g., fusion of ensemble of fault prone sensors) can be handled by Expandable BN (EBN) [2] that instantiates online for active variables using few generic dependencies *for single time/space /instance* (we call **individual**). **(b)** Changing (conditional probability distributions) CPDs for dynamic systems with interaction over individuals (e.g., human activity modeling with posture changes), is well represented by DBN [3] *when structure of individual remains the same*. **(c)** When only causal relations change (e.g., the best path to navigate among same set of nodes with different constraints), Dynamic Bayesian Mutinets (DBM) [4] or Spatio-Temporal BN (STBN) [7] can change the links *between the same set of variables, with [7] or without [4] temporal links*. In Multi-Dynamic Bayesian Nets (MDBN) [5] a subset of the relations are considered, *but relations between the same nodes cannot change*. We summarize the pros and cons of these BN frameworks in Table 1.

The real world systems or processes often evolve - neither with fixed dynamic model for the evolution process, nor with any prior predictability of what the evolution of the model will lead to (i.e., flexibility like one in the last row of Table 1).

**Table 1: Summary: Pros & Cons of Current BNs**

A: Expand nodes/relations using a generic causal structure
B: Causal links across different instances or individuals
C: Different set of causal relations considered
D: Different causalities between same 2 nodes in different instances
E: Shrinks or considers a subset of nodes/relations

| BN Frameworks | A | B | C | D | E |
|---|---|---|---|---|---|
| BN [1] | | | | | |
| EBN [2] | X | | X | | |
| DBN [3] | | X | | | |
| DBM [4] | | | X | X | |
| STBN [7] | | X | | X | |
| MDBN [5] | | | X | | X |
| This work | X | X | X | X | X |

**Example 1: Medical diagnosis modeling:** Medical diagnosis, even for the same health disorder, are often completely different due to different (a) symptoms and medical history or information, (b) their order and severity, (c) medical test results, (d) drugs applied, and (e) responses. Available medical evidences evolve continuously and unpredictably.

**Example 2: Modeling database retrieval and cache management:** In dynamic databases, indexing, caching and retrieval models change with several interrelated factors like, (a) current entities, (b) new entities, (c) query patterns, (d) relevance feedback, and (e) dynamically updated knowledgebase for several frequent users. Interactive queries of the users and dynamic retrieval/cache models try to match one another (for the best performance) in an intricate, continuous and unpredictable evolving fashion.

**Example 3: Video based incremental model building:** Smoothly changing 2D views of an object provides 3D queues for both human perception and automated 3D model building. Multiple views cause unpredictable continuous evolution in (a) the set of *visible* features, (b) spatio-temporal relations and constraints, (c) stochastic 2D to 3D mapping, and (d) incremental 3D model estimated until that instance.

These are from a generic domain of **evolvable problems** where probabilistic models continuously and

978-1-4244-2175-6/08/$25.00 ©2008 IEEE

Authorized licensed use limited to: Univ of Calif Riverside. Downloaded on September 14, 2009 at 15:42 from IEEE Xplore. Restrictions apply.

unpredictably evolve, in (a) different individuals and (b) inter-individual interactions (summery in Table 2). From Tables 1 and 2, none of the current BNs can represent these applications. We propose a novel Structure Modifiable Adaptive Reason-building Temporal BN (SmartBN) that supports all the above flexibilities (see the last rows of Table 1).

**Table 2: Summary: BN Flexibilities Required**

Legends are the same as in Table 1. Detailed in Sec 2.

| Examples | A | B | C | D | E |
|---|---|---|---|---|---|
| Medical Diagnosis | | X | X | | X |
| Database Retrieval | X | X | X | | |
| 3D Model Building | X | X | X | X | |

**Contributions:** **(1)** Focus on the complex domain of evolvable applications where current BNs are yet to be successful. **(2)** A novel SmartBN framework that can successfully represent this domain. **(3)** Performance validation of SmartBN in incremental 3D model building of vehicles from traffic video.

## 2. Where and Why Current BNs Fail?

We start with *illustrative* generic BN models of the above examples of evolvable applications.

**Medical Diagnosis System:** We extend the famous Asia BN model described in [1]. The statement is: *"The Shortening of breath (called dyspnoea, (D)) may be a symptom of lung cancer (C), tuberculosis (TB) or bronchitis (BR). Smoking (S) increases chance of cancer or bronchitis, while exposure to severe air pollution (P) may lead to cancer. A positive X-ray (X) indicates either TB or lung cancer. A recent visit of the patient to Asia (A) increases more chance of getting contagious TB. If the response (R) to initial drugs for either TB (DTB) or bronchitis (DBR) is negative, then cancer is decided and chemotherapy (CT) is prescribed"*. Intermediate variable TBorC for either TB or cancer reduces the BN complexity [1].

This generic set of causal structures is shown in the BN of Fig 1(a). But if the medical history of a patient is revealed gradually, BN needs evolution over the treatment period as shown in Fig 1 and Table 2.

**Database Retrieval/Cache Management:** BNs for relevance-feedback based database retrieval models is another current area of research [8]. In an example-based database retrieval model, the user perception (UP) effects query-example (QE). And QE and UP jointly affect the variable number of case-specific low-level features (LF). Higher-level features (HF) are the probabilistically combined version of the LFs. HFs and the indexing/similarity model (IM) of the database produce the retrieved results (RR) for the current iteration. User representation (UR) of a RR is defined by UP and that RR. Similarly, database representation (DR) of a RR comes from IM and that RR. UR and RR decide the relevance feedback (RF) by the user. The user pattern (PT) tries to align with indexing model IM based on RF. And dynamic cache (CH) tries to align to user perception UP based on RF and RR.

Generic causal relations of this model are shown in Fig 2(a). As the user and the database try to self-modify for best performance, BN structure changes, as shown

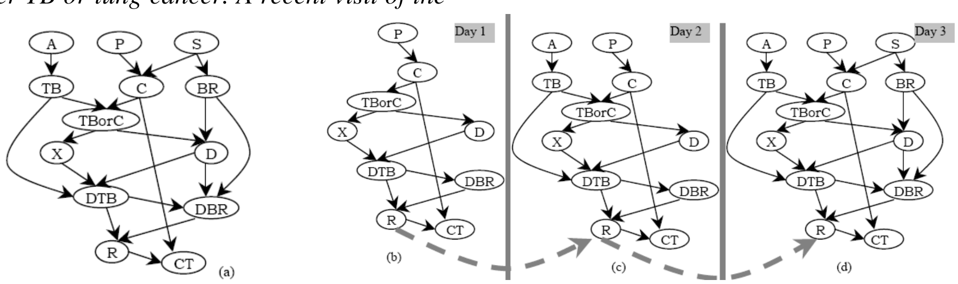


**Fig 1: Medical diagnostic system: (a)** Generic causal model. Doctor DR finds gradually **(b)** Day 1: Patient PT is non-smoker and never visited Asia. **(c)** Day 2: PT's close relatives went to Asia recently and so drug for TB (DTB) is applied. **(d)** Day 3: PT's best friend is a chain-smoker and passive smoking of PT leads to changed BN. Lingering effects of drugs is shown as gray arrows between responses (R's).

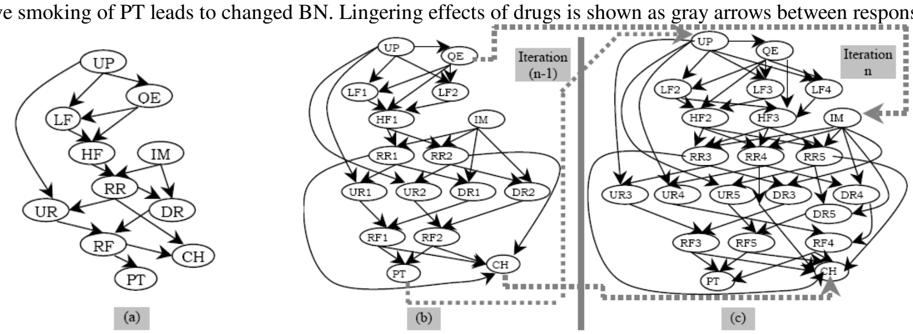


**Fig 2: Database retrieval/cache management: (a)** Generic causal model. Different retrieval iterations **(b)** Iteration 1: Search with low level features (LF1, LF2) and high-level feature (HF1) to retrieve 2 results. **(c)** Iteration 2: Modified search with (LF2, LF3, LF4) and (HF2, HF3) to retrieve 3 results. Self-modifications of user perception UP, indexing model IM and cache model CH are shown as gray arrows.

Authorized licensed use limited to: Univ of Calif Riverside. Downloaded on September 14, 2009 at 15:42 from IEEE Xplore. Restrictions apply.

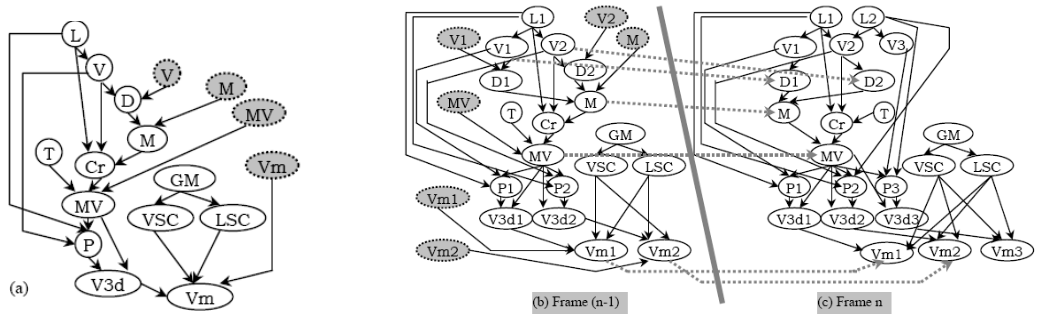


**Fig 3: Video based incremental 3D model building: (a)** Generic causal estimation model; and instantiations for 2 consecutive frames, **(b)** Frame (n-1): One line and two vertices visible. **(c)** Frame n: two lines and three vertices visible. New line L2 and vertex V3 may change the best path P1 or P2. Inter-frame causal links to ensure different smoothness constraints and to compute motion are shown as gray arrows.

for two iterations in Fig 2(b)-(c) and in Table 2. An intelligent user modifies his/her perception (UP) to match the indexing model (IM) using user pattern (PT) in last iteration. IM tries to match UP using the query example (QE) in the last iteration. And the cache-model (CH) dynamically changes over the iterations.

**Video based Incremental 3D Model Building:** In vehicle 3D model reconstruction from traffic video [6], the 2D vertices (V) estimated from the extracted lines (L). Global motion (M) of the vehicle in the current frame depends on the vertex displacements (D) that depend on the vertices (V) from consecutive frames. The motion and the lines in the object-origin define a 3D coordinate system (Cr). Matching this Cr to the directional templates (T) decides 2D-to-3D mapping vector (MV). MV and the lines (L) probabilistically define the best path (P). P's are used for estimation propagation starting from the origin - initialized to 3D location [0 0 0] in object-centered coordinates. Using the 2D location V, its best path P, and the 2D-to-3D scale-factors in MV, 3D vertex locations (V3d) for the current frame are computed. Finally, the incremental model parameters (Vm) are robustly estimated using the similarities of V3d with (a) corresponding parameters (Vm) in the incremental model learned till the last frame, and (b) two structural constraints, for vertices (VSC) and lines (LSC). VSC and LSC are computed from a generic 3D vehicle model (GM). To ensure robustness of the estimation process, we consider smoothness constraints in M's (smooth traffic), MV's (smoothly changing lane direction) and Vm's (i.e., 3D estimations cannot change abruptly).

Generic causal estimation model is shown in Fig 3(a). Due to self-occlusion only a subset of the features are *visible*, and this changes the BN structure across the frames, as shown in Fig 3(b)-(c) and Table 2.

**Why current BNs fail?:** The types of structural flexibilities needed in BN frameworks to represent each of the above evolvable applications are summarized in Table 2. Comparing with the Table 1, it is clear that none of the current BNs can work.

One strategy is to consider entire set of variables and causal links, incurring unnecessary burden of inactive variable before and after their active lives. This is neither scalable in time and space nor tractable even for a moderate size and complexity. We need a new data-driven online evolvable BN framework.

## 3. SmartBN: A Solution

An efficient elegant scalable method is to instantiate the probabilistic models online from a very few generic conditional relations (we call **causal templates**), based on evidences in hand. That is the key-idea of proposed Structure Modifiable Adaptive Reason-building Temporal BN (SmartBN) with key building blocks of following types of causal templates.

**Expandable Causal Templates: Individual Instantiations:** These are expert-defined generic causal relations describing any particular application (example: Fig 1(a), 2(a) and 3(a)). On the basis of the evidences available, only a subset (example: Fig 1) or several replications (example: Fig 2 and 3) of the relations are present in any particular instantiation. Unlike EBN templates [2], unique advantage is that the same type of nodes in same individual may have different causal relations (example: there are links between V1-D1, V2-D2, but not between V3-D3).

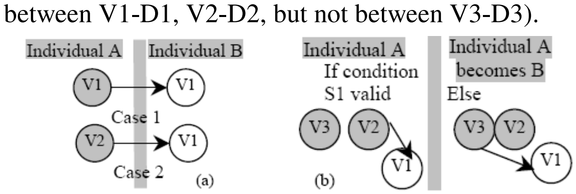


**Fig 4: SmartBN: Types of (a) Dynamic causal templates**, and **(b) Evolvable causal templates**: if condition S1 is valid, V2→V1, else V3→V1 although (V1, V2, V3) are present in both individuals.

**Dynamic Causal Templates: Inter-individual Relations:** These are causal relations between the same (case 1 in Fig 4(a)) or different (case 2 in Fig 4(a)) variables in two different individuals. Note, temporal variations and relations are only a special case where individuals are information from different times. Unlike DBN framework [3], structures may be different

Authorized licensed use limited to: Univ of Calif Riverside. Downloaded on September 14, 2009 at 15:42 from IEEE Xplore. Restrictions apply.

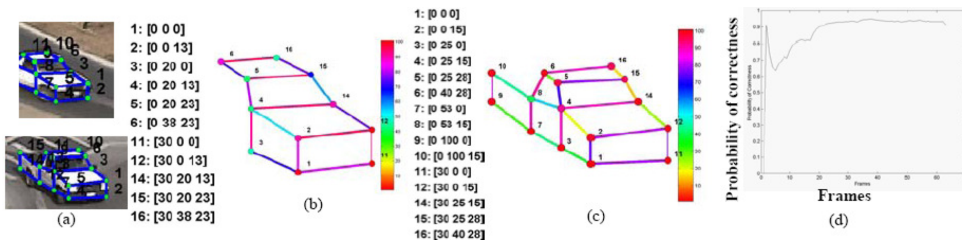


**Fig 6. SmartBN performance for incremental model building of vehicle from video: (a)** example frames, **(b)-(c)** corresponding incremental 3D models learned with parameter probabilities color-coded, and **(d)** learning trend for the entire 3D model.

across individuals. Examples of Case 1 of Fig 4(a) are: shaded arrows between (1) R's in Fig 1, (2) CH's in Fig 2, and (3) M's , MV's and Vm's in Fig 3. Examples of Case 2 of Fig 4(a) are: shaded arrows between (1) (QE and IM) and (PT and UP) in Fig 2, and (2) V's and D's in Fig 3.

**Evolvable Causal Templates: Changing Individuals:** In the real world, often some conditions change the expandable causal relations between the same set of nodes within single individual (Fig 4(b)) and thus transform individuals. The connections between P's and L's in Fig 3 may change, as the best paths can change due to appearance of new vertices/ lines or due to different noise-levels (e.g., the best path between vertices 1 and 6 in Fig 6(b) and 6(c) may be different due to appearance of new vertices 7-and 8).

**Interrelation Causal Templates: Changing Inter-individual Relations:** These are causal templates that *conditionally* change the interrelations between multiple individuals by changing dynamic causal relations between two (case 1 in Fig 5) or more (case 2 in Fig 5) individuals. Example of case 1 of Fig 5 is in Fig 3(b)-(c): absence of vertex V3 in frame (n-1) caused absence of displacement node D3 and link V3→D3 in frame n, although V3 and V1→D1 and V2→D2 are present. This is unique to SmarBN only.

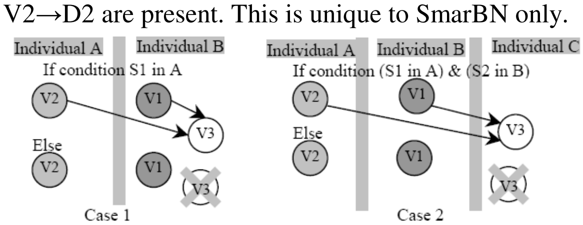


**Fig 5: SmartBN: Types of Interrelation causal templates: Case 1:** If condition S1 is valid, (V2 in A, V1 in B) →V3 in B; else V3 is absent in B. **Case 2:** If conditions S1 in A and S2 in B are valid, (V2 in A, V1 in B) →V3 in C; else V3 is absent in C.

## 4. SmartBN in 3D Model Building

To show the performance of SmartBN, we brief the incremental 3D vehicle model learning results from video. As seen from Fig 6, with the increasing number of extractible 2D lines and vertices (comparing 6(b) and 6(c)), probability of models parameters (shown in 6(b)-(c) as color-coded) and the learned 3D model (Fig 6(d)) increase. The 3D model parameter values are superimposed. The initial peak in the learning trend in Fig 6(d) is because of too less evidences and hence the model is overestimated. The model probability could reach as high as 0.95 and thus validates that the structural scalability of SmartBN does not affect its probabilistic reasoning capability.

## 5. Conclusions and Future Work

In this paper, we focus on a domain of continuously evolving applications from several areas and show that the current forms of EBN, DBN, STBN, DBM, and MDBN cannot model the *simultaneous* flexibility in number of random variables and structure of causal relations between them over different objects or space or time. We propose a data-driven scalable flexible BN framework, Structure Modifiable Adaptive Reason-building Temporal BN (SmartBN) that can broaden the horizon of BNs and can represent evolving applications. Performance of SmartBN in incremental 3D model building from video is encouraging and we plan to apply SmartBN to other applications in future.

**Acknowledgements:** This work was supported in part by NSF grants 0551741 & 0622176. The information contents do not reflect the position or policy of the US Government.

## References


[1] Korb, K.B., Nicholson, A.E.: Bayesian Artificial Intelligence. Chapman and Hall (2004).

[2] Kim, Z.: Multi-View 3-D Object Description With Uncertain Reasoning and Machine Learning. Ph.D. Thesis, Dept. of CS, Univ. of Southern California, Los Angeles (2001).

[3] Murphy, K.: Dynamic Bayesian Networks: Representation, Inference and Learning. Ph.D. Thesis. Dept. of CS, Univ. of California, Berkeley, California, USA (2002).

[4] Bilmes, J.A.: Dynamic Bayesian Multinets. Uncertainty in Art. Intelligence. (2000) 38-45.

[5] Filali, K., Bilmes, J.A.: Multi-Dynamic Bayesian Networks. Adv. NIPS, Dec 2006.

[6] Ghosh, N., Bhanu, B.: Incremental Vehicle 3D Modeling From Video. Intl. Conf. Pattern Recognition. 3 (2006) 272-275.

[7] Tucker, A., et. al: A Spatio-Temporal Bayesian Network Classifier For Understanding Visual Field Deterioration. J. AI Med. 34(2) (2005) 163-177.

[8] Campos, L.M., et al: Implementing Relevance Feedback in the Bayesian Network Retrieval Model. J. American Soc. Info. Sc. Tech. 54(4) (2003) 302-313.

[9] Friedman, N., Koller, D.: Being Bayesian About Network Structure. J. Mach. Learn. 50 (2003) 95-126.


Authorized licensed use limited to: Univ of Calif Riverside. Downloaded on September 14, 2009 at 15:42 from IEEE Xplore. Restrictions apply.