Supplementary material for

Learning transition models of biological regulatory and signaling networks from noisy data

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1 Performance of LGTS and PLGTS models

This section includes the performance of LGTS and PLGTS models on the noiseless MAPK cascade network and phosphate regulatory network data set in the form of figures. Networks obtained are presented as extended Petri net structures. The results shown here are also presented in the paper as table 1 and 2. Figure 1 and 2 shows the inferred networks after the application of LGTS and PLGTS models on noiseless MAPK cascade and phosphate regulatory network data set. Highlighted control arcs (with red color) in the network represent the incorrect control arcs found in the network. It can be seen in figures that PLGTS model outperforms LGTS model in terms of identification of incorrect control places for the transitions in the inferred network.

2 Connection between Petri net and DBN

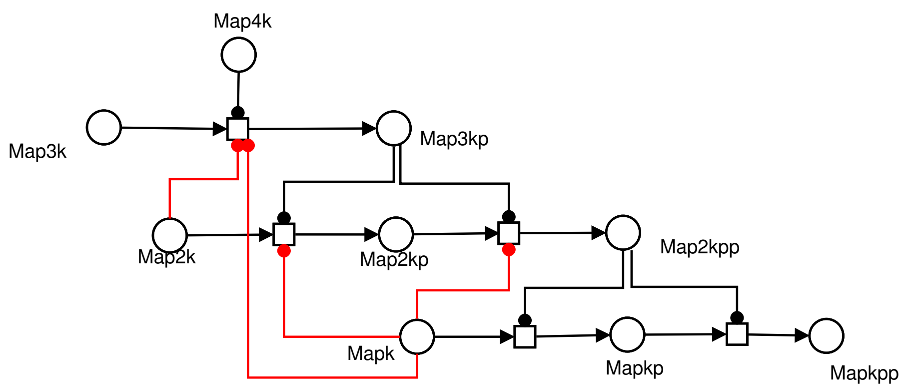
Consider the chemical reaction where reactant A produce product C in the presence of catalyst B. That is,

$$A \xrightarrow{B} C$$

Petri net structure of this reaction is given in figure 3 (a). Now in DBN representation, node C(t+1) will be conditionally dependent on nodes A(t) and B(t) as it requires the presence of both for its own production. Node A(t+1) will be conditionally dependent on node A(t) since A(t+1) will be ON if A(t) was ON and has not been consumed in the reaction (which may happen if other necessary factors are not fulfilled, leading to reaction failure) while it will be OFF if A(t) has been consumed to produce C(t+1). Node B(t+1) will not be conditionally dependent on node B(t) as it will not be consumed in the reaction and its value will remain same irrespective of whether the reaction fired or not. The DBN structure of this chemical reaction is also shown in figure 3 (b).

However, our approach in the paper could only find out the probability and edges between those nodes which are involved in the transition (i.e., edges between A(t), B(t) and C(t+1)). And could not find the probability of a node dependent on itself at different time points (i.e., the probability of A(t+1) given A(t)). Thus, DBN representation seems to be more general than the Petri net representation and there can be a DBN representation for every Petri net that produce the same markings from some initial marking.

(a) Network obtained from LGTS model on noiseless MAPK data set



(b) Network obtained from PLGTS model on noiseless MAPK data set

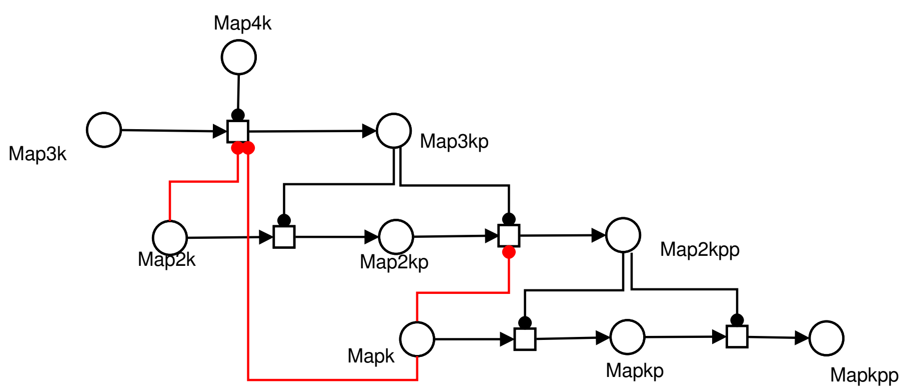
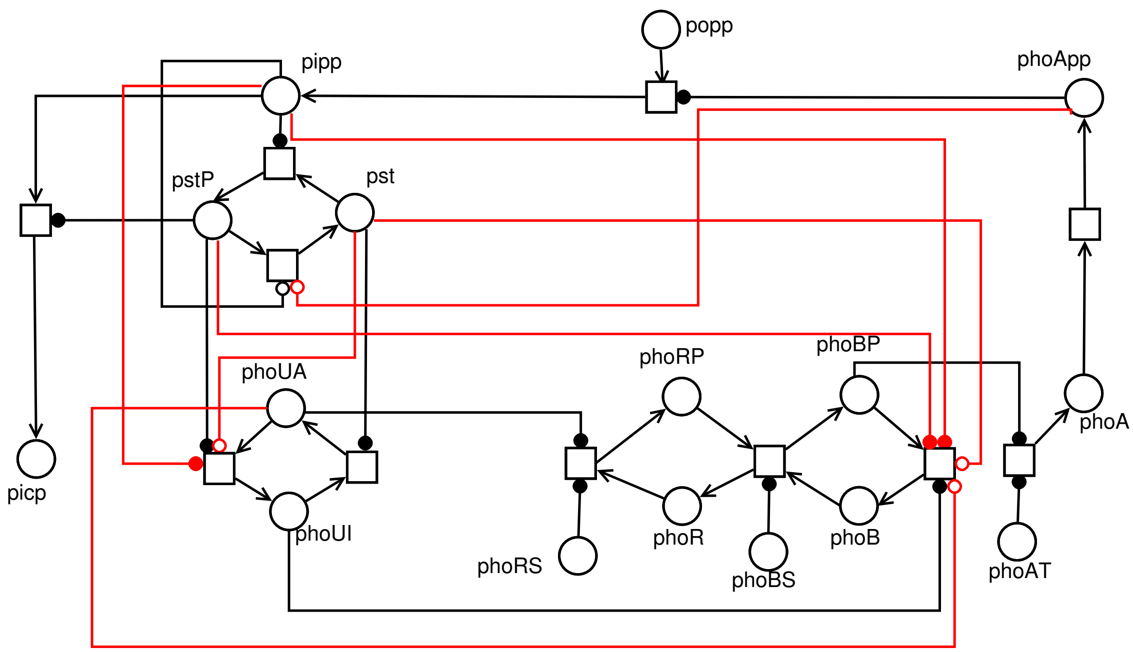


Figure 1: Petri net structure of network obtained from LGTS and PLGTS models on noiseless MAPK data set

(a) Network obtained from LGTS model on noiseless Phosphate regulatory dataset



(b) Network obtained from PLGTS model on noiseless Phosphate regulatory dataset

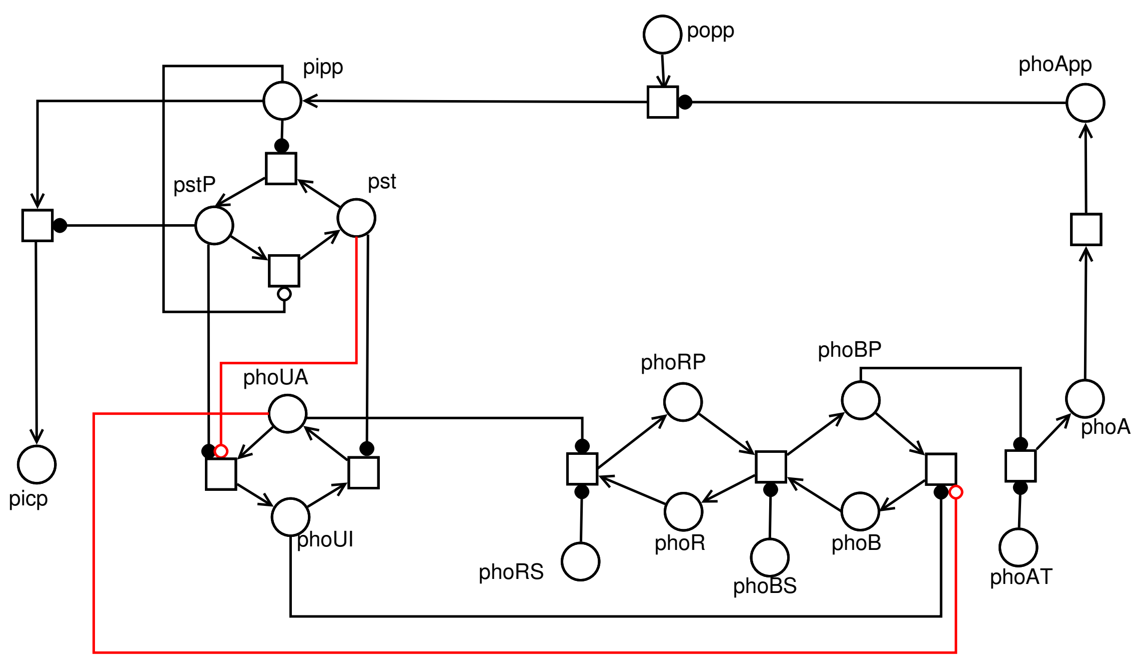


Figure 2: Petri net structure of network obtained from LGTS and PLGTS models on noiseless Phosphate regulatory network data set

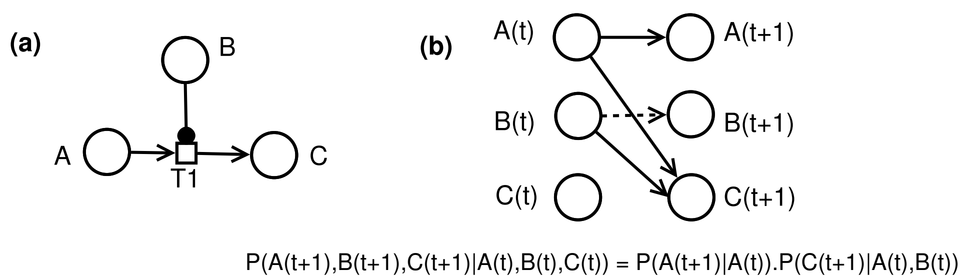


Figure 3: Connection between (a) Petri net and (b) DBN. Input places of transitions in Petri net become parent nodes in DBN. Nodes involved in conditional distribution in DBN are shown as solid edges.