A Computational Bayesian Approach to Ternary Network Estimation (ternarynet)

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1 Introduction

This document describes *ternarynet*, which implements a computational Bayesian algorithm to estimate a ternary network from perturbation data. We strongly recommend reading the paper, *Fitting Boolean Networks from Steady State Perturbation Data* (Almudevar et al. 2011) before proceeding with this vignette.

2 Getting Started

First begin by downloading and installing the ternarynet package.

> library(ternarynet)

**parallelFit function**

The *ternarynet* package contains a parallel implementation of the replica exchange algorithm for fitting ternary network models. The **parallelFit** function takes the following arguments:

- **experiment_set** data frame containing five columns:
  - *i_exp* an experiment index: an integer from 0 to $N_{\text{exp}} - 1$, where $N_{\text{exp}}$ is the number of experiments.
  - *i_node* a node index: an integer from 0 to $N_{\text{node}} - 1$, where $N_{\text{node}}$ is the number of nodes.
  - *outcome* a value of -1, 0, or +1, denoting a particular outcome for that node in that experiment
  - *value* a cost for obtaining that outcome. For instance, if the cost function is the Hamming distance, and the observed outcome is +1, the cost would be would be +2, +1, or 0 for an outcome of -1, 0, or +1, respectively.
  - *is_perturbation* a Boolean value (or a value of 0/1) denoting whether this outcome is due to an applied perturbation or not.

- **max_parents** maximum number of parents allowed for each node

- **n_cycles** maximum number of Monte Carlo cycles

- **n_write** number of times to write output during the run
T_lo T for lowest-temperature replica
T_h T for highest-temperature replica
target_score run will terminate if this is reached
n_proc number of replicas
logfile filename for log file
n_thread number of openMP threads to run per process; default=1
init_parents initial parents; randomize if null
init_outcomes initial outcomes; set to '.' if null
exchange_interval steps between replica exchanges; default=1000
adjust_move_size_interval steps between move size adjustments, default=7001
max_states maximum number of states to propagate to find a repetition; default=10
callback callback function, should take one integer argument (the replica number),
    used to call set.seed with different seed for each replica

The return value is a list with an element for each replica. Each element is itself
a list of the best unnormalized score, normalized score (unnormalized score divided by
product of number of nodes and number of experiments), list of parents for each node,
and array describing the transition rule, giving the outcome of a node for each possible
configuration of parent nodes.

Examples

The following shows a subset of the simple model regulatory network given in Example
1 of Reference 1 (nodes 1-4 only). There are four nodes and eight experiments (the first
four rows of Table 4). The cost function for each possible outcome is the Hamming
distance with the observed steady-state outcome, given a persistent perturbation. The
output corresponds with the parents and transitions described on page 13 of Almudevar
et al. (2011).

> library(ternarynet)
> i_exp <- as.integer(c(0,0,0, 0,0,0, 0,0,0, 0,0,0, 1,1,1, 1,1,1, 1,1,1, 1,1,1, 1,1,1, 1,1,1, 1,1,1))
\[ i_{\text{node}} <- \text{as.integer}(c(0,0,0, 1,1,1, 2,2,2, 3,3,3, 0,0,0, 1,1,1, 2,2,2, 3,3,3, 0,0,0, 1,1,1, 2,2,2, 3,3,3, 0,0,0, 1,1,1, 2,2,2, 3,3,3)) \]

\[ \text{outcome} <- \text{as.integer}(c(-1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1, -1,0,1)) \]

\[ \text{value} <- c(0,1,2, 0,1,2, 0,1,2, 0,1,2, 2,1,0, 2,1,0, 2,1,0, 0,1,2, 2,1,0, 2,1,0, 2,1,0, 0,1,2, 0,1,2, 0,1,2, 0,1,2) \]

\[ \text{is_perturbation} <- \text{c(TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE, FALSE,FALSE,FALSE, FALSE,FALSE,FALSE, TRUE,TRUE,TRUE)) \]

\[ \text{indata} <- \text{data.frame}(i_{\text{exp}},i_{\text{node}},\text{outcome},\text{value},\text{is_perturbation}) \]

\[ \text{results} \leftarrow \text{parallelFit}(\text{indata}, \text{max_parents}=1, \text{...}) \]
+ n_cycles=100000,
+ n_write=10,
+ T_lo=0.001,
+ T_hi=2.0,
+ target_score=0,
+ n_proc=1,
+ logfile='try.log')

> lowest_temp_results <- results[[1]]
> print('Unnormalized score: ')

[1] "Unnormalized score:"

> print(lowest_temp_results$unnormalized_score)

[1] 0

> print('Normalized score: ')

[1] "Normalized score:"

> print(lowest_temp_results$normalized_score)

[1] 0

> print('Parents: ')

[1] "Parents:"

> print(lowest_temp_results$parents)

[,1]
[1,]  3
[2,]  0
[3,]  1
[4,]  2

> print('Outcomes: ')
> print(lowest_temp_results$outcomes)

[,1] [,2] [,3]
[1,] 1 0 -1
[2,] -1 0 1
[3,] -1 0 1
[4,] -1 0 1

Subsequent fits may be started using the network from a previous fit as the initial conditions, as in the following example (the initial network in the case already has a score of 0).

> results <- parallelFit(indata,
+ max_parents=1,
+ n_cycles=10,
+ n_write=10,
+ T_lo=0.001,
+ T_hi=2.0,
+ target_score=0,
+ n_proc=1,
+ logfile='try.log',
+ init_parents=lowest_temp_results$parents,
+ init_outcomes=lowest_temp_results$outcomes)

> lowest_temp_results <- results[[1]]
> print('Unnormalized score: ')

[1] "Unnormalized score:"

> print(lowest_temp_results$unnormalized_score)

[1] 0

> print('Normalized score: ')

[1] "Normalized score:"


```r
> print(lowest_temp_results$normalized_score)

[1] 0

> print('Parents: ')

[1] "Parents:"

> print(lowest_temp_results$parents)

 [,1]
[1,] 3
[2,] 0
[3,] 1
[4,] 2

> print('Outcomes: ')

[1] "Outcomes:"

> print(lowest_temp_results$outcomes)

 [,1] [,2] [,3]
[1,]  1  0  -1
[2,] -1  0  1
[3,] -1  0  1
[4,] -1  0  1

> 

3 Session Info

> sessionInfo()
```