Comparing association network algorithms for reverse engineering of large-scale gene regulatory networks: synthetic versus real data

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1 INTRODUCTION

Of the various problems one can encounter in Systems Biology, that of reverse engineering gene regulatory networks from high-throughput microarray expression profiles is certainly one of the most challenging for a number of reasons. First, the number of variables that come into play is very high, of the order of the thousands or tens of thousands at least, and there is normally no sufficient biological knowledge to restrict the analysis to a subset of core variables for a given biological process. Second, the number of gene expression profiles available is typically much less than the number of variables, thus making the problem underdetermined. Third, there is no standard model of the regulatory mechanisms for the genes, except for a generic cause-effect relationship between transcription factors and corresponding binding sites. Fourth, little is known (and no high-throughput measure is available) about the post-transcriptional modification and on how they influence the regulatory pattern we see on the microarray experiments. In spite of all these difficulties, the topic of reverse engineering of gene regulatory networks is worth pursuing, as it provides the biologist with phenomenologically predicted gene–gene interactions.

Many are the methods that have been proposed for this scope in the last few years, like Bayesian networks (Friedman et al., 2000), linear ordinary differential equations (ODEs) models (Yeung et al., 2002), relevance networks (Butte and Kohane, 1999; D’haeseleer et al., 1998) and graphical models (Kishino and Waddell, 2000; de la Fuente et al., 2004; Magwene and Kim, 2004; Schäfer and Strimmer, 2005).

The aim of this work is to compare a few of these methods, focusing in particular on the last two classes of algorithms, that reconstruct weighted graphs of gene–gene interactions. Relevance networks look for pairs of genes that have similar expression profiles throughout a set of different conditions, and associate them through edges in a graph. The reconstruction changes with the ‘similarity measure’ adopted: popular choices for gene networks are covariance-based measures like the Pearson correlation (PC) (Butte and Kohane, 1999; D’haeseleer et al., 1998), or entropy-based like the mutual information (MI) (Butte and Kohane, 2000; D’haeseleer et al., 1998). While PC is a linear measure, MI is non-linear. These simple pairwise similarity methods are computationally tractable, but fail to take into account the typical patterns of interaction of multi-variate datasets. The consequence is that they suffer from a high false discovery rate, i.e. genes are erroneously associated while in truth they only indirectly interact through one or more other genes.

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In order to investigate a more realistic setting, the aforementioned methods were applied to a publicly available dataset of 445 gene expression profiles for 4345 genes of *Escherichia coli*. Since a benchmark graph in this case is obviously unknown, in order to evaluate the algorithms we used the network of transcription factors–binding sites (TrF-BS) available in Salgado *et al.* (2006). Needless to say, due to the complexity of the transcriptional and post-transcriptional regulatory mechanisms of a living organism, we expect the TrF-BS network to be only partially reflected in the inferred network. Quite remarkably, though, we find that for all algorithms the 3071 edges of the TrF-BS graph are markedly over-represented among the highest weighting edges of the reconstructed network, thus showing that (i) transcription factors indeed contribute to the regulation of gene expression; (ii) the inference algorithms have some predictive power also in real systems (although the number of false positives remains unavoidably very high).

Furthermore, if we create an artificial dataset starting from the TrF-BS graph of *E.coli*, we can also compare the predictive power on an *in silico* model with that on the *in vivo* system with equal amount of information. We will see that in the regime of much less measurements than variables the differences are not so large. As a byproduct, we also have an indicative estimate of how much our artificial model is a simplification of a real transcriptional regulatory network.

## 2 METHODS

### 2.1 The artificial network

The model we used to generate artificial gene expression datasets is the reaction kinetics-based system of coupled non-linear continuous time ODEs introduced in Mendes *et al.* (2003). The expression levels of the gene mRNAs are taken as state variables, call them $x_i$, $i = 1, \ldots, n$. The influence on the transcription of each gene due to the other genes is described by a (sparse) matrix of adjacencies $A = (a_{ij})$ and the rate law for the mRNA synthesis of a gene is obtained by multiplying together the sigmoidal-like contributions of the genes identified as its inhibitors and activators. Consider the $i$-th row of $A$, $i = 1, \ldots, n$ and choose randomly a sign to its non-zero indexes. Denote by $A_{j1}, \ldots, A_{jk}$ the indexes with assigned positive values (activators of the gene $x_i$) and with $k_1, \ldots, k_s$ the negative ones (inhibitors of $x_i$). The ODE for $x_i$ is then

$$
\frac{dx_i}{dt} = V_i \prod_{j \notin \{k_1, \ldots, k_s\}} \left( 1 + \frac{v_{ij}}{s_{ij} + \theta_{ij}} \right) \prod_{k \in \{k_1, \ldots, k_s\}} \frac{\theta_{jk}}{s_{jk} + \theta_{jk}} - \lambda_i x_i,
$$

where $V_i$ represent the basal rate of transcription, $\theta_{ij}$ (respectively $\theta_{jk}$) the activation (resp. inhibition) half-life, $v_{ij}$ (resp. $v_{ik}$) the activation (resp. inhibition) Hill coefficients (in our simulations: $v_{ij}, v_{ik} \in \{1, 2, 3, 4\}$) and $\lambda_i$ the degradation rate constants. The ODE (1) always tends to a steady state, which could be $0$ or a (positive) saturation value. When $x_i(0) > 0$, the abundance $x_i(t)$ remains positive during the entire time course, hence the solution is biologically consistent.

As for the topology of $A$, we shall consider two classes of directed networks widely used in literature as models for regulatory networks: scale-free (Barabási and Albert, 1999) and random (Erdős and Rényi, 1959).
2.1.1 Data generated For the artificial network (1), a gene expression profile experiment at time \( t \) corresponds to a state vector \( [x_1(t), \ldots, x_n(t)] \) obtained by numerically integrating (1). For the purpose of reconstructing the network of gene–gene interactions from expression profiles, one needs to carry out multiple experiments, in different conditions, typically performed perturbing the system in many different ways. We shall consider the following cases of perturbations:

1. randomly chosen initial conditions in the integration of (1), plus gene knockout obtained setting to 0 the parameter \( V_i \) of the respective differential equation, as in Mendes et al. (2003);
2. only randomly chosen initial conditions in the integration of (1); and
3. the following types of measurements:
   1. steady state measurements;
   2. time-course experiments, in which the solution of the ODE is supposed to be measured at a certain (low) sampling rate.

The numerical integration of (1) is carried out in MATLAB. In all cases, a Gaussian measurement noise is added to corrupt the output.

2.2 Pearson correlation and partial Pearson correlation

Methods based on PC relevance networks were proposed already in D’haeseleer et al. (1998). If to each gene \( i \) we associate a random variable \( X_i \), whose measured values we denote as \( x_i(t) \) for \( t = 1, \ldots, m \), the PC between the random variables \( X_i \) and \( X_j \) is

\[
R(X_i, X_j) = \frac{\sum_{t=1}^{m} (x_i(t) - \bar{x}_i)(x_j(t) - \bar{x}_j)}{(n - 1)\sqrt{\sum_{t=1}^{m} (x_i(t) - \bar{x}_i)^2} \sqrt{\sum_{t=1}^{m} (x_j(t) - \bar{x}_j)^2}},
\]

where \( \bar{x}_i, \bar{x}_j \) and \( \bar{x}_i, \bar{x}_j \) are sample means and variances of \( x_i(t) \) and \( x_j(t) \) over the \( m \) measurements.

Since correlation alone is a weak concept and cannot distinguish between direct and indirect interactions. (e.g. mediated by a common regulation gene), an algorithm for network inference can be improved by the use of partial correlations (de la Fuente et al., 2004). The minimum first order partial correlation between \( X_i \) and \( X_j \) is obtained by exhaustively conditioning the pair \( X_i, X_j \) over all \( X_k \). If \( k \neq i,j \) which explains all of the correlation between \( X_i \) and \( X_j \), then the partial correlation between \( X_i \) and \( X_j \) becomes 0 and the pair \( X_i, X_j \) is conditionally independent given \( X_k \). When this happens, following Edwards (2000) we say that the triple \( X_i, X_j, X_k \) has a Markov property: on an undirected graph genes \( i \) and \( j \) are not adjacent but separated by \( k \). This is denoted in Edwards (2000) as \( X_i \perp X_j \mid X_k \). In formulas, the minimum first order PPC is

\[
R_{C_1}(X_i, X_j) = \min_{k \neq i,j} \{R(X_i, X_j \mid X_k) \},
\]

where

\[
R(X_i, X_j \mid X_k) = \frac{R(X_i, X_j) - R(X_i, X_k)R(X_j, X_k)}{(1 - R^2(X_i, X_k))(1 - R^2(X_j, X_k))}.
\]

If \( R_{C_1}(X_i, X_j) \geq 0 \) then exists \( k \) such that \( X_i \perp X_j \mid X_k \). Sometimes conditioning over a single variable may not be enough, and one would like to explore higher order PPCs. The minimum second order PPC for example is given by

\[
R_{C_2}(X_i, X_j) = \min_{k, l \neq i,j} \{R(X_i, X_j \mid X_k, X_l) \},
\]

with

\[
R(X_i, X_j \mid X_k, X_l) = \frac{R(X_i, X_j \mid X_k) - R(X_i, X_k \mid X_l)R(X_j, X_k \mid X_l)}{(1 - R^2(X_i, X_k))(1 - R^2(X_j, X_k))}.
\]

and so on for higher order PPCs. Since the computation is exhaustive over all \( n \) genes, the computational cost of the algorithm for the \( k \)-th order minimum PPC is of the order of \( O(n^k) \), and it becomes quickly prohibitive for \( k \geq 2 \), if \( n \) is of the order of the thousands.

The weight matrix \( R \) can be used to rank the \( (n^2 - n)/2 \) possible (undirected) edges of the graph. The use of PPC allows to prune the graph of many false positives computed by PC alone. However, the information provided by PC and PPC is one of independence or conditional independence, i.e. a low value of PC and PPC for a pair \( X_i, X_j \) guarantees that an edge between the two nodes is missing. A high value of the quantities \( R(X_i, X_j) \) and \( R_{C_1}(X_i, X_j) \) does not guarantee that \( i \) and \( j \) are truly connected by an edge, as \( R_{C_1}(X_i, X_j) \) may be small or vanish.

In de la Fuente et al. (2004) it is shown how to choose a cutoff threshold for the weight matrices and how to combine together the effect of \( R, R_{C_1} \) and \( R_{C_2} \).

2.3 Graphical Gaussian models

When the \( n \times n \) matrix \( R(X_i, X_j) \) is invertible, and we can assume that the data are drawn from a multivariate normal distribution, then the exhaustive conditioning over \( n - 2 \) genes can be expressed explicitly. Denote \( \Omega = R^{-1} \) the concentration matrix of elements \( \Omega = (\omega_{ij}) \). Then the partial correlation between \( X_i \) and \( X_j \) is

\[
R_{C_{ij}}(X_i, X_j) = \frac{\omega_{ij}}{\sqrt{\omega_{ii}\omega_{jj}}},
\]

When \( R \) is not full rank, then the small-sample stable estimation procedure of Schäfer and Strimmer (2005) can be used. To compute \( R_{C_{ij}} \), we used the R package GeneNet version 1.0.1, available from CRAN (http://cran.r-project.org).

2.4 Mutual information and conditional mutual information

In an association network, alternatively to PC and PPC, one can use the information-theoretic concept of MI (Butte and Kohane, 2000; Gardner and Faith, 2005; Margolin et al., 2006), together with the notion of conditional independence to discern direct from indirect dependencies. Given a discrete random variable \( X \), taking values in the set \( \mathcal{H}_X \), its entropy (Shannon, 1948) is defined as

\[
H(X) = - \sum_{\phi \in \mathcal{H}_X} p(\phi) \log p(\phi),
\]

where \( p(\phi) \) is the probability mass function \( p(\phi) = \mathbb{P}(X = \phi), \phi \in \mathcal{H}_X \). The joint entropy of a pair of variables \( X_i, X_j \), taking values in the sets \( \mathcal{H}_{X_i}, \mathcal{H}_{X_j} \), respectively, is

\[
H(X_i, X_j) = - \sum_{\phi \in \mathcal{H}_{X_i}, \psi \in \mathcal{H}_{X_j}} p(\phi, \psi) \log p(\phi, \psi),
\]

while the conditional entropy of \( X_j \) given \( X_i \) is defined as

\[
H(X_j \mid X_i) = H(X_j, X_i) - H(X_i).
\]

The MI of \( X_i, X_j \) is defined as \( I(X_i, X_j) = H(X_i) - H(X_i \mid X_j) \) and can be explicitly expressed as

\[
I(X_i, X_j) = \sum_{\phi \in \mathcal{H}_{X_i}, \psi \in \mathcal{H}_{X_j}} p(\phi, \psi) \log \frac{p(\phi, \psi)}{p(\phi)p(\psi)} \geq 0.
\]

When the joint probability distribution factorizes, the MI vanishes:

\[
p(\phi, \psi) = p(\phi)p(\psi) \Rightarrow R(X_i, X_j) = 0.
\]

The MI conditioned with respect to a third variable \( X_k \) is:

\[
I(X_i, X_j \mid X_k) = H(X_i, X_k) + H(X_j, X_k) - H(X_k) - H(X_i \mid X_k, X_j).
\]

or, equivalently,

\[
I(X_i, X_j \mid X_k) = H(X_i, X_k) + H(X_j, X_k) - H(X_k) - H(X_i \mid X_j, X_k).
\]
All pairs of nodes can be conditioned exhaustively on each of the remaining \( n-2 \) nodes and the minimum of such CMIs

\[
I_c(X_i; X_j) = \min_{i \neq j} I(X_i; X_j | X_k)
\]

can be taken as a measure of conditional independence. When there exists a \( X_i \) that explains the whole MI between \( X_i \) and \( X_j \), then the triplet has the Markov property

\[
R(X_i; X_j | X_k) = 0 \iff X_i \perp X_j | X_k.
\]

implying \( I_c(X_i; X_j) = 0 \), otherwise \( I_c(X_i; X_j) > 0 \).

Just like for the PC and PPC cases, the two conditions (2) and (3) can be used to construct the graph of the gene network. \( I \) and \( I_c \) can also be combined together, and possibly with a cutoff threshold (computed e.g. through a bootstrapping method). An alternative algorithm to implement the Markov property is the so-called DPI and consists in dropping the edge corresponding to the minimum of the triplet \( I(X_i, X_j), I(X_i, X_k) \) and \( I(X_j, X_k) \) for all possible triplets \( i \neq j \neq k \). This method is shown in Margolin et al. (2006) to prune the graph of many false positives.

Denote \( I_{DPI} \) the matrix obtained by applying the DPI. Although \( I_{DPI} \) and \( I_c \) derive from the same notion, the information they provide is not completely redundant. In the computation of \( I \) and \( I_c \) we used the B-spline algorithm of Daub et al. (2004). The matrix \( I_c \) obtained in this way is quite similar to the MI one gets from the Gaussian Kernel method used in Margolin et al. (2006), see Supplementary Material.

While the definition of CMI can be extended to higher number of conditioning variables, from a computational point of view this becomes unfeasible for \( n \) of the order of thousands: the time complexity of our algorithm for complete data matrices is \( O(n^3 mp^q) \), where \( p \) is the spline order and \( q \) is the number of bins used.

### 3 RESULTS

#### 3.1 Synthetic data

In order to evaluate the algorithms, we compare each (symmetric) weight matrix with the corresponding adjacency matrix \( A \) and calculate the (standard) quantities listed in Table 1.

The Receiver Operating Characteristic (ROC) and the Precision versus Recall (PvsR) curves measure the quality of the reconstruction. To give a compact description for varying \( m \), the Area Under the Curve (AUC) of both quantities will be used. The ROC curve describes the trade-off between sensitivity and the false positive rate (1-specificity). An AUC(ROC) close to 0.5 corresponds to a random forecast, AUC(ROC) < 0.7 is considered poor, 0.7 ≤ AUC(ROC) < 0.8 fair and AUC(ROC) ≥ 0.8 good. For gene networks, as \( A \) is generally sparse, the ROC curve suffers from the high number of false positives. The PvsR curve instead is based only on comparing true edges and inferred edges, and therefore highlights the precision of the reconstruction (Margolin et al., 2006). All the quantities we consider as well as the ROC and the PvsR curves are based on sorting the edge weights (in absolute values for PC, PPCs and GGM) and on growing the network starting from the highest weight down to the lowest one. Fixing a cutoff threshold only means altering the tail of the curves, thus we shall not make any such choice, but explore the entire range of values for the edge weights.

In Figure 1, the results for reconstructions of random and scale-free networks of 100 genes with the different similarity measures (\( R, R_{C1}, R_{C2}, R_{GGM}, I, I_c \) and \( I_{DPI} \)) are shown for different numbers \( m \) of measurements. AUC(ROC), AUC(PvsR) and the number of TP for a fixed value of acceptable FP (here 20) are displayed in the three columns.

By comparing the first two rows of Figure 1 it is possible to examine the influence of the network topology on the reconstruction. Under equal conditions (type and amount of experiments), all the algorithms performed better for random networks, confirming that they are easier to infer than scale-free ones (de la Fuente et al., 2004). Also another network parameter, the average degree, is influencing the performance of the algorithms: the predictive power is higher for sparser networks than for less sparse ones (see Section 2 of the Supplementary Material).

If we now focus the attention on the scale-free topology (the most similar to known regulatory networks), it can be seen from the graphs that the performances of the reconstructions are much higher with knockout perturbations (rows 2–3) than for data produced without knockouts (row 4). This suggests that knockouts [i.e. node suppression on (1)] help in exploring the network structure, while perturbing only the initial conditions contributes very little predictive information.

Moreover, when perturbing the system with knockouts, steady state measurements (row 2) are able to generate good reconstructions with much less samples than time-course experiments (row 3), in agreement with the results of Bansal et al. (2007). For steady states, the performances of the algorithms improve increasing \( m \) up to \( n \), then stabilize (for some, like GGM, even decrease). For time-course data, instead, the graphs tend to level off only when each gene has been knocked out once, regardless of the number of samples taken during the time series. This can be seen on the third row of Figure 1, where the AUCs keep growing until 1000 samples (corresponding to 100 time series each contributing 10 samples) and only then tend to stabilize (data beyond 1000 samples are not shown in Fig. 1). The same trend can be observed increasing the number of samples per series (data not shown). Learning a network by means of time series alone (without any knockout) is very difficult as can be deduced from the low values of AUCs achieved in the fourth row of Figure 1. Notice, however, that these values get much worse (essentially random) if we consider no-knockout and steady state samples.

As for the different algorithms, the PPCs perform well in all conditions, and are significantly improving performances with respect to PC for both AUC(PvsR) and TP for fixed FP. On the contrary, applying the DPI to MI [with a tolerance of 0.1, see Margolin et al. (2006)] only slightly improves the precision of the MI. Since the DPI simply puts to zero the weights of the

<table>
<thead>
<tr>
<th>TP (true positives)</th>
<th>= correctly identified true edges</th>
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<tbody>
<tr>
<td>FP (false positives)</td>
<td>= spurious edges</td>
</tr>
<tr>
<td>TN (true negatives)</td>
<td>= correctly identified zero edges</td>
</tr>
<tr>
<td>FN (false negatives)</td>
<td>= not recognized true edges</td>
</tr>
<tr>
<td>recall (or sensitivity)</td>
<td>= TP/(TP + FN)</td>
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<tr>
<td>specificity</td>
<td>= TN/(TN + FP)</td>
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<td>precision</td>
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Fig. 1. Evaluating the reconstructions via $R$, $RC_1$, $RC_2$, $RC_{all}$, $I$, $IC$ and $IDPI$ algorithms on 100 gene artificial networks for increasing numbers of measurements. Top row: random topology, knockout perturbations and steady state measurements. Second row: scale-free topology, knockout perturbations and steady state measurements. Third row: scale-free, knockout and time-course experiments. Fourth row: scale-free, only initial conditions perturbations and time-course experiments. On the two time courses 10 (equispaced) samples are taken on each time course. The x-axis label ‘N. of measurements’ refers to the total number of samples taken (for example 200 means 200 experiments of steady state type, but only 20 experiments on the two time courses). Left column: AUC(ROC). Central column: AUC(PvsR). Right column: number of TP for a number of FP equal to 20. Values shown are means over 10 repetitions.
edges it considers false positives, one should not forget that DPI is penalized with respect to the other measures when computing AUC(ROC). Like PPCs, GGM gives good average results, but looks promising especially for time-course experiments, where also CMI is far superior than MI and DPI.

Finally, it is important to remark that the results we obtained for a network of 100 genes are qualitatively and quantitatively similar to those for larger gene networks: as an example in the Supplementary Material a scale-free network of 1000 genes yields AUCs that are comparable to those shown in Figure 1 for an equal ratio $m/n$.

### 3.2 E.coli network inference

We downloaded the *E.coli* gene expression database $M^{3D}$ ‘Many Microbe Microarrays Database’ (build E coli_v3_Build_1 from http://m3d.bu.edu, T. Gardner Lab, Boston University). This dataset consists of 445 arrays from 13 different collections corresponding to various conditions, like different media, environmental stresses (e.g. DNA damaging drugs, pH changes), genetic perturbations (upregulations and knockouts) and growth phases. The experiments were all carried out on Affymetrix GeneChip *E.coli* Antisense Genome arrays, containing 4345 gene probes. A global RMA normalization was performed on the data prior to network inference. All methods described above were applied, except $R_{CI}$, which is computationally very heavy for thousands of genes and behaves in much the same way as $R_{C}$. Calculating CMI took us ~12 days on a 3 GHz processor. $I_{DPI}$ was computed from $I$ with a tolerance equal to 0.3 (the tolerance suggested in Margolin et al. (2006), 0.1, prunes 95.75% of the TrF-BS edges).

As mentioned before, we chose as ‘true’ matrix the *E.coli* K12 transcriptional network compiled in the RegulonDB database, version 5.6 (Salgado et al., 2006), from which we derived a direct graph of 3071 interactions. As the number of possible undirected edges is 9,437,340, this matrix is too sparse for any of the previous statistics to be meaningful, e.g. AUCs(ROC) are all around 0.6. Furthermore, biologically the transcription regulation cannot be expected to be manifestly dominant over all other processes that determine the gene expression levels in a living organism. Nevertheless, if we look at the weights assigned to the TrF-BS edges (‘true’ edges) by the reconstruction algorithms, we see that they are significantly overrepresented in the highest weighting region (right part of the graph in Fig. 2) that in the medium/low weight ones (center/left in Fig. 2), regardless of the similarity measure adopted. To confirm the validity of our approach, we applied a randomization to the $M^{3D}$ dataset and then inferred the network with the best reconstruction algorithm (GGM). In this case, as one would expect, the TrF-BS edges are uniformly distributed on the bins (rand $R_{C}$ in Fig. 2).

If we focus only on the highest weighting bin of each reconstruction algorithm, the concordances on the identified edges (i.e. the intersection of TP) among the algorithms are shown in Table 2. Notice the high degree of concordance between correlation and MI.

In absolute terms, of course, there is a huge number of edges with high weights not corresponding to any TrF-BS interaction (i.e. FP), reflecting the complexity of the gene expression regulation program.

#### 3.3 Artificial versus in vivo data, given a network

Starting from the *E.coli* TrF–BS direct graph, it is possible to create an artificial dataset using the model (1) and compare the predictive power of the algorithms on synthetic data with the previous real expression profiles. For this scope we generated the same amount of synthetic data (445 measurements), describing experiments of steady state knockout type. The same type of score based on coarse grain binning shown in Figure 2 is shown in Figure 3 for these synthetic data. Clearly the predictive power has grown in average, although the difference is not so drastic as one could have expected. Similarly, the concordances of TP in the top bins
network inference. In short, structural perturbations are more efficient than 'structurally' perturbed, e.g. by means of node suppressions. For the networks generated with the model (1), we find that otherwise not detectable. AUC(ROC) around 0.9 are reached only by MI, PC and GGM in the steady state knockout simulations. Conditioning is useful to improve the false discovery rate, and the TP it identifies are to a large extent different from those detected without conditioning. Of all algorithms tested only second order PPC and CMI are too computationally intensive to be used in a truly large network (tens of hundreds of thousands of genes). MI, CMI and DPI depend heavily on the implementation algorithm, and, at least in our B-spline implementation, on the underlying model of probability distribution (for time-course experiments the quality of the reconstruction improves considerably with the pre-application of a rank transform to the data). Correlations instead, are much less sensitive. For example replacing PC with Spearman correlation yields no substantial difference. The best performances versus runtime are achieved by the GGM algorithm. Sparse networks are easier to identify than dense (or less sparse) ones, regardless of the algorithms used, see Supplementary Material. Even with $m \ll n$ (realistic situation), using steady state knockout experiments all algorithms have a decent predictive power.

5 CONCLUSION

For a real network like the one of E.coli, under the (biologically plausible) assumption that gene expression reflects transcriptional regulation through the TrF-BS interactions, we find that the predictive power of essentially all algorithms is certainly non-zero, and that GGM ‘guesses’ a remarkably high number of edges, with respect to the other similarity measures, but also in absolute value, taking into account that in this case $m/n \sim 1/10$. Using the same graph to compare our artificial network and the ‘true’ network of the in vivo system we do not see a dramatic difference in the predictive power between the two. This could be simply due to the above-mentioned low ratio $m/n$.

Other interesting observations are the following:

- After a certain threshold $n_0 \geq n$ the inference ratio of all algorithms tends to stabilize. To improve the predictive capabilities, other types of perturbations should probably be used (like e.g. simultaneous multiple knockouts, external stimuli, etc.).
- Other interesting observations are the following:
the precision is very low and the number of false positives
unavoidably very high.

Conflict of Interest: none declared.

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