**FASTGapFill**: efficient gap filling in metabolic networks

Ines Thiele*, Nikos Vlassis and Ronan M. T. Fleming

Luxembourg Centre for Systems Biomedicine, University of Luxembourg, Luxembourg, L-4362

ABSTRACT

**Motivation**: Genome-scale metabolic reconstructions summarize current knowledge about a target organism in a structured manner and as such highlight missing information. Such gaps can be filled algorithmically. Scalability limitations of available algorithms for gap filling hinder their application to compartmentalized reconstructions.

**Results**: We present FASTGapFill, a computationally efficient tractable extension to the COBRA toolbox that permits the identification of candidate missing knowledge from a universal biochemical reaction database (e.g., Kyoto Encyclopedia of Genes and Genomes) for a given (compartmentalized) metabolic reconstruction. The stoichiometric consistency of the universal reaction database and of the metabolic reconstruction can be tested for permitting the computation of biologically more relevant solutions. We demonstrate the efficiency and scalability of FASTGapFill on a range of metabolic reconstructions.

**Availability and implementation**: FASTGapFill is freely available from http://thielegroup.eu.

**Contact**: ines.thiele@uni.lu

**Supplementary information**: Supplementary data are available at Bioinformatics online.

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1 INTRODUCTION

A biomolecular network reconstruction summarizes biochemical, physiological and genomic knowledge in a mathematically structured electronic format (Palsson, 2006). It can be converted into a computational model, and predictions have been used to accelerate biotechnological and biomedical discoveries (Oberhardt et al., 2010). The predictive capacity and accuracy of a model depend on the comprehensiveness and biochemical fidelity of the reconstruction, with respect to the underlying biochemistry. The comprehensiveness of a genome-scale metabolic reconstruction can be improved by using the model to detect and fill network gaps (Rolfsson et al., 2011). Similarly, reconstruction fidelity can be improved by using the model to detect reconstruction stoichiometry inconsistent with biochemistry (Gevorgyan et al., 2008) or reactions inconsistent with steady state flux (Vlassis et al., 2014).

Existing gap-filling algorithms, reviewed by Orth and Palsson (2010), become intractable in high dimensions. Decompartmentalization of genome-scale compartmentalized metabolic networks reduces their dimension, rendering gap filling tractable (Rolfsson et al., 2011). However, this approach underestimates the amount of missing information because it connects reactions that would normally not co-occur in the same cellular compartment.

We present FASTGapFill, the first scalable algorithm capable of efficiently detecting and filling network gaps in compartmentalized genome-scale models. FASTGapFill draws on, and extends, fastcore (Vlassis et al., 2014), an algorithm to approximate the cardinality function to identify a compact flux consistent model, in which all reactions carry a non-zero flux in at least one flux distribution. FASTGapFill allows integrating all three notions of model consistency, namely, gap-filling, flux consistency and stoichiometric consistency in a single tool.

2 METHODS

**Formulation of the gap-filling problem.** In the metabolic gap-filling problem (Reed et al., 2006), one starts with a computational metabolic model, $M$, that contains at least one blocked reaction, which, though desired, does not admit a non-zero steady state flux. From a universal database, e.g. the Kyoto Encyclopedia of Genes and Genomes (KEGG) (Kanehisa and Goto, 2000), a search is made for at least one reaction that needs to be added to fill at least one gap in the model, such that at least one formerly blocked reaction can carry flux. Among other criteria, it may also be desirable to compute a compact flux consistent model, where the number of added universal reactions is minimal. A specific instance of this problem occurs in metabolic modeling, although our algorithm is applicable for any biochemical network model with gaps.

**Computing a compact flux consistent model.** We repurposed the recently developed fastcore algorithm (Vlassis et al., 2014) to compute a near-minimal set of reactions that need to be added to an input metabolic model $M$ to render it flux consistent. fastcore takes input $M$ and a core set of reactions $C \subseteq M$. Then, it greedily expands $C$ by computing a set of modes of $M$ whose overall support contains the whole of $C$ and a minimal set from $M \setminus C$. This is achieved by a series of $L_1$-norm regularized linear programs that optimize a relaxed version of an (intractable) integer program under cardinality constraints (Vlassis et al., 2014). Our implementation efficiently identifies blocked reactions.

**Preprocessing to generate a global model.** A cellularly compartmentalized metabolic model ($S$) without blocked reactions ($B$), where $S \cup B = M$, is expanded by a universal metabolic database $U$ (e.g., KEGG), such that a copy of $U$ is placed in each cellular compartment of $S$ (including the extracellular space), to generate $SU$. For each metabolite occurring in a non-cytosolic compartment, a reversible intercompartmental transport reaction is added. For each extracellular metabolite, an exchange reaction is added. The sum of the latter two reaction sets ($X$) is added to $SU$ to generate a global model, which is extended with solvable blocked reactions ($B_s \subseteq B$), that is, reactions that were previously flux inconsistent but become flux consistent when added to the global model. In the extended global model ($SUX$), all reactions are flux consistent. Note that not all blocked reactions $B$ may be solvable, and thus, they will not be present in $SUX$. All reactions of $S$ and $B_s$ represent the core set.

*To whom correspondence should be addressed.*
### 3 IMPLEMENTATION

An open source, MATLAB (Mathworks, Inc.), implementation of fastGapFill is available as a cross-platform desktop computer extension to the openCOBRA toolbox (Schellenberger et al., 2011).

### 4 DISCUSSION

We applied fastGapFill to five metabolic models (Table 1), demonstrating its broad applicability and scalability for various sizes of the gap-filling problem. Alternate gap-filling solutions can be computed by changing weightings on non-core reactions in the preprocessed problem. Note that all candidate metabolic and transport reactions are hypotheses requiring experimental validation (Rollinson et al., 2011). Our implementation provides an openCOBRA (Schellenberger et al., 2011) compatible version of the KEGG reaction database; however, any other universal reaction database could be used with fastGapFill, so long as the same input format is maintained and care is taken to correctly identify identical metabolites. fastGapFill is the first scalable approach to identify candidate missing knowledge in compartmentalized metabolic reconstructions, and the approach is applicable to any form of biochemical network gap-filling problem.

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**Conflict of Interest**: none declared.

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### Table 1. Gap filling of metabolic reconstructions on a standard desktop computer (Dell, Intel Core i5, 16 GB RAM, 64 bit)

| Model name                  | Thermotoga maritima (Zhang et al., 2009) | Escherichia coli (Feist et al., 2007) | Synechocystis sp. (Nogales et al., 2012) | sIEC (Sahoo and Thiele, 2013) | Recon 2 (Thiele et al., 2013) |
|-----------------------------|------------------------------------------|---------------------------------------|-----------------------------------------|---------------------------------|-------------------------------|
| S                                          | 418 × 535                                | 1501 × 2232                           | 632 × 731                               | 834 × 1260                      | 3187 × 5837                   |
| SUXa                                      | 14020 × 31 566                           | 21 614 × 49 355                       | 28 174 × 62 866                         | 48 970 × 109 522                | 58 672 × 132 622              |
| Compb                                      | 2                                        | 3                                     | 4                                       | 7                               | 8                             |
| B                                         | 116                                      | 196                                   | 132                                     | 22                              | 1603                          |
| Bj                                         | 84                                       | 159                                   | 100                                     | 17                              | 490                           |
| Number of gap-filling reactions            | 87                                       | 138                                   | 172                                     | 14                              | 400                           |
| Ipreprocessing (S)                       | 52                                       | 237                                   | 344                                     | 1003                            | 5552                          |
| IfastGapFill ($)                          | 21                                       | 238                                   | 435                                     | 194                             | 1826                          |

*The dimensions are given as metabolites × reactions.

Comp, compartments.

*Preprocessing includes computing the flux consistent metabolic model, merging of UX for all compartments of S and adding solvable blocked reactions Bj.

Note: Equal weighting of all reactions was used. See Supplementary Table S1 for candidate gap-filling solutions.
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