HAL
open science

Data integration in logic-based models of biological mechanisms

Benjamin A Hall, Anna Niarakis

To cite this version:

Benjamin A Hall, Anna Niarakis. Data integration in logic-based models of biological mechanisms. Current Opinion in Systems Biology, 2021, 28, pp.100386. 10.1016/j.coisb.2021.100386 . hal-03515653

HAL Id: hal-03515653

https://hal.science/hal-03515653

Submitted on 6 Jan 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Systems Biology

Data integration in logic-based models of biological mechanisms

Benjamin A. Hall[1] and Anna Niarakis[2,3]

Abstract

Discrete, logic-based models are increasingly used to describe biological mechanisms. Initially introduced to study gene regulation, these models evolved to cover various molecular mechanisms, such as signaling, transcription factor cooperativity, and even metabolic processes. The abstract nature and amenability of discrete models to robust mathematical analyses make them appropriate for addressing a wide range of complex biological problems. Recent technological breakthroughs have generated a wealth of high-throughput data. Novel, literature-based representations of biological processes and emerging algorithms offer new opportunities for model construction. Here, we review up-to-date efforts to address challenging biological questions by incorporating omic data into logic-based models and discuss critical difficulties in constructing and analyzing integrative, large-scale, logic-based models of biological mechanisms.

Addresses

[1] Department of Medical Physics and Biomedical Engineering, UCL, London, UK

[2] GenHotel, Univ. Évry, University of Paris-Saclay, Genopole, 91025, Évry, France

[3] Lifeware Group, Inria Saclay-île de France, Palaiseau, 91120, France

Corresponding author: Niarakis, Anna (anna.niaraki@univ-evry.fr)

Current Opinion in Systems Biology 2021, **28:**100386

This review comes from a themed issue on **Big Data Acquisition & Analysis (2021)**

Edited by **Julio Banga** and **Jan Hasenauer**

For complete overview of the section, please refer the article collection - Big Data Acquisition & Analysis (2021)

Available online 25 September 2021

https://doi.org/10.1016/j.coisb.2021.100386

2452-3100/© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Keywords

Logic-based models, Boolean models, Executable models, Qualitative dynamical modeling, Omic data integration, *In silico* simulations, Formal verification.

Introduction

Logic-based models have made significant contributions to our understanding of a wide range of biological processes in health and disease. Initially introduced in the 60s to describe gene regulatory circuits [1–3], logic-based models have evolved substantially over the past five decades to cover various biological processes, such as signaling cascades, ion channels, coregulation of transcription factors, and even metabolism. With the growing body of data available due to technological breakthroughs, new methods are being developed to integrate different biological scales and expand the size and complexity of discrete models. In addition, efforts to create formalized, large-scale representations of network 'maps' open avenues for rapidly repurposing these datasets to serve as scaffolds for qualitative models [4].

Logic-based models use logical operators, such as AND, OR, and NOT, to describe the functions that govern the regulation of the biological entities. While detailed mechanistic knowledge is not a prerequisite, the type of regulation (positive or negative) between the biological entities and the directionality of these regulations is necessary to construct the regulatory graph [5]. In the logical formalism, genes, proteins, and other biomolecules are assigned discrete values that correspond to activity thresholds (binary values for Boolean networks [BNs], multivariate values for logical models), and logical rules define the evolution of the system in the next time step. Time is implicitly modeled using updating schemes that, together with the logical rules, define the emergent behavior of the system [6,7]. The precise quantitative relationship between model variables and experimental observables is model dependent and needs to be considered during the model building process.

In silico simulations of the logic-based discrete models give insights into the dynamics of the modeled system and allow in-depth analysis, including the searching of 'attractors': terminal states of the system such as steady states or cycles [8]. Simple attractors represent fixed points that correspond to the system's stable states. These states can be linked to cellular decision-making processes, such as apoptosis, cell proliferation, migration, and chemotaxis. Complex attractors represent terminal cycles that can be linked to biological oscillations, such as, for example, the p53 MDM2 interactions [9–11]. The absence of parameters makes logic-based models suitable for large-scale biological networks where little or no kinetic information is available.

Nevertheless, as their size and complexity scale up, their analysis can prove to be challenging.

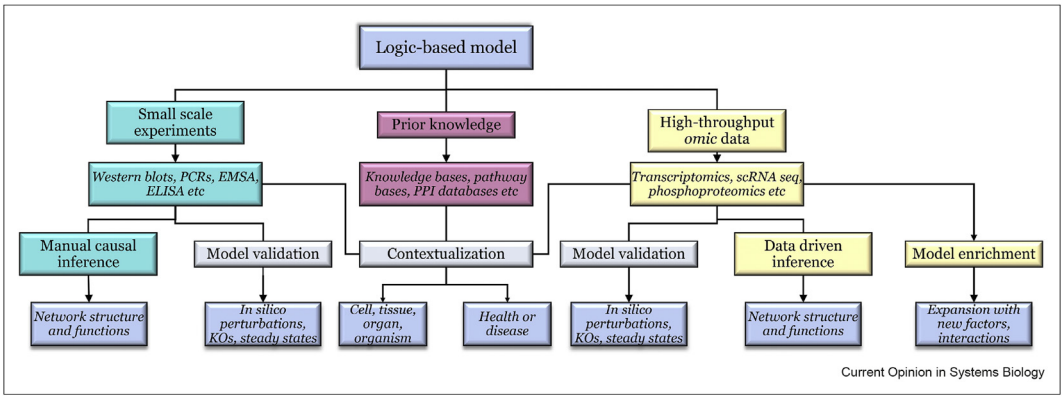
Technological advancements including high-throughput methods have led to an overwhelming amount of biological data. Such data have created a pressing need to develop tools and methodologies that could integrate omic data into the modeling pipelines. These new approaches include the use of omic data in combination with small-scale experiments and prior knowledge for (i) model enrichment, pointing to new interactions and regulators, (ii) model contextualization, adding specificity in terms of data origin and type (species, body fluid, cell type, tissue, single-cell data, bulk, disease state, treatment, healthy condition, and so on), (iii) model validation, showcasing that the model can reproduce known behaviors of the system of interest, and (iv) as source input to infer network structure and functions (Figure 1).

High-throughput data integration into logic-based models

Efforts to combine high-throughput data with discrete logic-based modeling depend heavily on the model purpose and the data availability and include model enrichment, validation, and contextualization. A typical approach consists of using omic data to expand existing models with entities of interest that can be measurable and comparable in different conditions. Early attempts to combine high-throughput data with logic-based models consisted mainly of using data as a guide to model enrichment, identifying key genes and biomolecules to include in the model. An example of such an approach is the building of a logic-based model to study mast cell activation in the context of allergy, combining high-throughput proteomics and prior knowledge [12]. To build the regulatory graph, besides literature mining, the authors used proteomic data, pointing to novel SLP76 interactants identified for the first time in mastocytes [13]. A combination of small-scale experiments, such as quantitative polymerase chain reaction (PCR), Western blots, and electrophoretic mobility shift assay (EMSA), together with data from genome-wide assays, such as RNA sequencing and chromatin ImmunopreciPitation (ChIP)-sequencing, was used to assemble a comprehensive regulatory network to study the reprogramming of pre-B cells into macrophages [14]. An iteration of model predictions and *in vitro* validation led to the update of the model with new knowledge and a better understanding of B-cell reprogramming mechanisms. In the same line, researchers developed a methodology that integrates several -omics datasets to identify candidate genes, serving as seeds for network modeling. They analyzed multiomics data from the consensus molecular subtypes [15,16] study of colorectal cancer to expand a previously built generic cell fate decision network [17].

In many studies, omic data are used as a source of biomarker signatures compared against stable states to validate phenotypic outcomes. This requires discretizing the measured data, using statistical thresholds such as the p-value or fold change. In this case, the regulatory graph of the discrete model is usually built manually through curation of the literature, text mining, and pathway database interrogation. The logical formulae describing specific mechanisms of gene activation are derived from the results of small-scale experiments. The modeler curates the relevant literature and uses the experiments to infer causality and mechanistic details, where possible. Then, different types of omic data are analyzed and compared against the model behavior for validation. This step includes data discretization using statistical thresholds to facilitate the comparison with the discrete nature of the logic-based model results. Recent examples include the enrichment of a logical

Figure 1



Different data types and sources and their uses in the inference and analysis of logic-based models.

model of macrophage polarization to describe cancer cell—macrophage interactions and its validation using microarray expression data from *in vitro* coculture experiments [18,19]. A similar methodology is used for the building of a logical model for cancer cell invasion and migration. Alongside model building, researchers propose matching transcriptomics data to the attractors and validating the model on cell line experiments [20]. Going one step further and focusing on the role of ion channels in cancer, an executable model of osmotic regulation and membrane transport was proposed predicting behavior from expression data [21,22]. In addition to considering large data sets, this model expands the family of biological processes beyond just expression and gene activation to include the coordinated activities of biomolecules (in this case ions) that are not under direct control by single genes.

In a recent commentary, the need for personalized models and the challenges that lie in incorporating high-throughput data into mechanistic dynamic models were highlighted [23]. An example of this is the framework developed to tailor logical models to a particular biological sample. The approach focuses on integrating mutation data, copy number alterations, and expression data (transcriptomics or proteomics) into logical models [24]. Using these data, the researchers propose a logical model to study the mechanisms of resistance to BRAF inhibition between melanomas and colorectal cancers. The model was built using literature mining and pathway integration and was contextualized for 100 melanoma and colorectal cell lines using available omics data, including mutations and RNAseq data [25]. Cell-specific logic-based models have also been used to recapitulate experimentally tested dynamic proteomic changes and phenotypic responses in diverse acute myeloidleukemia (AML) cell lines treated with a variety of kinase inhibitors [26]. To improve patient stratification, researchers assembled a network of logical relationships linking genes that are mutated frequently in AML patients and contextualized the model with genomic data inferring relevant patient-specific clinical features [27]. In each of these cases, even where the studied cancer type was the same, different models reflect not only the biology and specific questions being studied but also the data used to build the model and the predictions that could be made. This underlines the importance of knowing the role data integration plays in model building.

Data-driven discrete model inference

Although high-throughput datasets offer new ways to build and analyze models following bottom-up approaches, reverse engineering methods can also be applied to infer models from experimental data. Different algorithms have been developed to reconstruct logic-based models, and specifically BNs, from high-throughput data. There exist two broad categories: combinatorial optimization methods, which include integer or answer set programming (ASP) and allow for full exploration of the search space to identify the model that best explains the experimental data, and methods that implement heuristic approaches. The first category has the drawback of not scaling well due to computational explosion, while the second one tends to focus on specific conditions and stable states to ease the calculation burden. In broad terms, automated inference of BNs and functions from data can be a daunting task due to the uncertainty of the data itself and also to the large number of unknowns regarding structure and functions that need estimation. Moreover, identifying the most suitable data type and available datasets for model training adds to the task, as they need to be different from the data used for inference. It should be noted that the experimental ability to resolve biologically important expression or concentration differences will impact the results; datasets that are prone to noise or that concern low-expressed genes may introduce bias by excluding important pathways.

Recently, the caspo time series (caspo-ts) method [28,29], which allows learning of BNs from phosphoproteomic time series data given a prior knowledge network (PKN), was applied to data from four breast cancer cell lines (BT20, BT549, MCF7, UACC812) [28]. Based on ASP and model checking, the method could handle a large PKN with 64 nodes and 170 edges [30]. Another popular software for building logic-based models of signaling networks using prior knowledge and phosphoproteomic data is CellNOptR. CellNOptR supports multiple formalisms, from BNs to differential equations, in a common framework [31,32]. GABNI (genetic algorithm based boolean network inference) is a method that searches for an optimal Boolean regulatory function by exploiting a mutual information-based BN inference. If this step fails to find an optimal solution, then a genetic algorithm (GA) is applied to search an optimal set of regulatory genes on a broader solution space [33]. Boolean omics network invariant-time analysis (BONITA) is a new algorithm for signal propagation, signal integration, and pathway analysis capable of modeling heterogeneity in transcriptomic data. The logical rules of the model are inferred by the GA and are refined by local search. Application of BONITA pathway analysis to previously validated RNA-sequencing studies identifies additional relevant pathways in *in-vitro* human cell line experiments and *in-vivo* infant studies [34]. Single-cell expression data have also been used to infer the underlying model of blood development from the mesoderm. The expression of 40 genes, measured using quantitative reverse transcription-polymerase chain reaction (qRT-PCR) data in 3934 cells, was discretized and used to infer a BN consisting of 20 transcription factors, giving insight into the independent roles of Hox and Sox in Erg activation [35]. Lastly, BTR, an algorithm for training asynchronous BNs with single-cell expression data using a novel

Boolean state space scoring function, was recently proposed. BTR refines existing BNs and infers new by improving the match between model prediction and expression data [36].

Scalability in inference and analysis of logic-based models

Understanding complex biological processes, such as immunometabolism, the tumor microenvironment, chronic or acute inflammation, or autoimmunity, requires models that do not comprise only a handful of nodes but can be adapted accordingly to incorporate hundreds of nodes and reactions. Advancements in the field reflect the tendency to scale up in terms of size and complexity to create models of more realistic performance. Recently, the development of the tool CaSQ bridged the gap between static and dynamic representations of disease mechanisms, with the inference of large-scale BNs from molecular interaction maps [37]. The automated inference of large-scale BNs creates new challenges in analyzing these models, pushing the limits of the existing tools and methodologies. Commonly used software such as GINsim [38] can handle Boolean and multivariate logic-based models; however, the attractor's search can be challenging when scaling up, relying on model reduction techniques to deal with large systems.

Several platforms offer different approaches to dealing with large complex systems, focused on different problem areas. Cell Collective [39] efficiently handles large-scale BNs for simulations but does not offer attractors search. In contrast, BoolNet, an R/Bioconductor package, offers a collection of options for the analysis of BNs and a set of heuristics for attractors search when the size and the complexity of the model are considerably large [40]. These heuristics focus on retrieving stable states in lieu of searching the whole state space and significantly reducing the calculation burden, although the results are limited to analyzing stable states. Bio model analyzer (BMA) [41,42] focuses on analyzing stable states and, more particularly, fixed points, offering several highly scalable algorithms for model analysis, including stability proof, cycle searching, and linear temporal logic [43–45]. The specialization of tools emphasizes the importance of commonly agreed standards for model storage.

In parallel, progress has been made in developing hybrid and multiscale integrative modeling frameworks, connecting different formalisms, and generating new insights from the emergent, combined properties. FlexFlux, an open-source java software, combines metabolic and regulatory networks based on the identification of steady states. These steady states are further used as constraints for metabolic flux analyses using flux balance analysis (FBA) [46]. A multiscale framework that couples cell cycle and metabolic networks in yeast was proposed, integrating BNs of a minimal yeast cell cycle with a constraint-based model of metabolism. Models are implemented in Python using the BooleanNet and COBRApy packages and are connected using Boolean logic. The methodology allows for the incorporation of interaction data and validation through -omics data [47].

Community efforts for the reproducibility of discrete models in biology

Recent studies have raised concerns about reproducibility in various scientific fields. In computational systems biology, efforts have been made to identify the problem and propose strategies to tackle it [48]. The curation and annotation of logical models (CALM) initiative emerged to promote reproducibility, interoperability, accessibility, and reusability of the discrete biological models [49]. The initiative promotes reproducibility by linking model components to the underlying experimental articles using proper identifiers such as BioModels.net Qualifiers[1], and interoperability by promoting the use of the SBML-Qual format, an extension of the SBML Level 3 standard compatible with the representation of qualitative models of biological networks [50]. Furthermore, the CoLoMoTo Interactive Notebook developed by the community relies on Docker and Jupyter technologies to provide a unified and user-friendly environment to edit, execute, share, and reproduce analyses of qualitative models of biological networks via streamlining of tools that do not necessarily use standard formats, circumventing compatibility issues [51].

In Table 1, we list the tools mentioned in the previous sections, with a brief description of their features, the environment, and their capacity of supporting annotations.

New methods for formal analysis of large-scale logic-based models

In this section, we highlight recent developments regarding formal analysis. The methodologies presented here address problems inherent to larger and more complex models.

One issue that arises as networks become larger is the role of timings in the control of cellular function. While timing effects can be accounted for in small models using synchronous or asynchronous update schemes as more genes are introduced, this may not be a scalable approach. Ignoring potential timing effects however may obscure important model properties. The most permissive boolean networks (MPBNs) approach is a promising formal method that addresses the fact that both synchronous and asynchronous dynamical interpretations of BNs can miss some predictions of behaviors observed in similar quantitative systems. The MPBNs approach formally guarantees not to miss any

[1] https://co.mbine.org/standards/qualifiers.

Table 1

Brief overview of relevant modeling software and their main features.

Tool	Features	Environment	SBML-Qual support	Annotation support
Tools for automated inference of logic-based models				
CaSQ	Inference of BNs from molecular interaction maps	Python	Yes	Yes
Caspo-ts	Inference of BNs from time series omic data	Python	No	No
CellNOpt	Inference of BNs from time series omic data	R/Bioconductor	Yes	No
BONITA	Inference of BNs from transcriptomic data	R/Bioconductor	No	No
Tools for analysis of logic-based models				
GINsim	Logical network analysis; *in silico* simulations; reduction functionality; possibility for exhaustive attractors' search; updating scheme: synchronous and asynchronous	Java	Yes	Yes
Cell Collective	BN analysis; real-time *in silico* simulations; topological analysis; updating scheme: synchronous and asynchronous	JavaScript, web-based	Yes	Yes
BoolNet	BN analysis; *in silico* simulations; different options for attractors' search including heuristics; updating scheme: synchronous and asynchronous	R/Bioconductor	Yes	No
Bio model analyzer (BMA)	Stability analysis; *in silico* simulations; exhaustive search for attractors; linear temporal logic; updating scheme: synchronous	Web-based, optional CLI	No	Yes
Frameworks for integrative analysis of logic-based models with constrained based metabolic models				
FlexFlux	BN and FBA analysis	R/Bioconductor	Yes	No
BooleaNet and COBRApy	BN and FBA analysis	Python	No	No

BN, Boolean network; CLI, Command line interface; FBA, flux balance analysis.

behavior achievable by a quantitative model following the same logic. Moreover, MPBNs significantly reduce the complexity of dynamical analysis, allowing for modeling genome-scale networks. One limitation of the approach can be the generation of overapproximated dynamical representations, with only small subsets of the corresponding trajectories effectively observed [52].

The control of BNs offers the possibility to delineate interconnected pathways and specify conditions to determine a functional outcome, offering a way to focus on a smaller subset of nodes that possess important properties over the whole network. Researchers compute a minimal subset of nodes (Cmin) in recent work that allows a BN to be driven from any initial state in an attractor to an attractor of interest by a single step perturbation of Cmin. In their method, they decompose the network into modules, compute the minimal control on the projection of the attractors to these modules, and then compose the results to obtain the global Cmin [53].

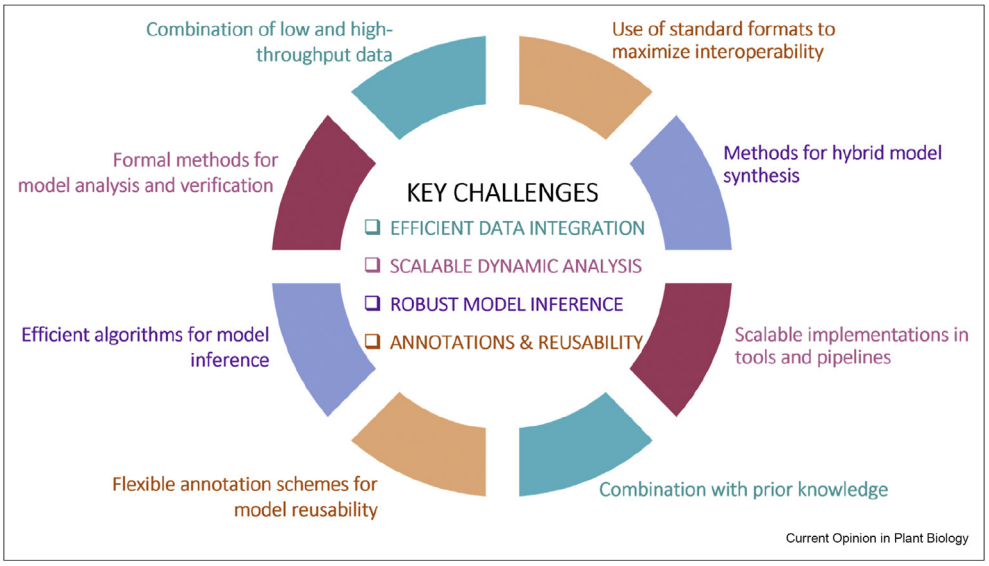
Finally, as models become larger, state space expands and the potential for rare transitions that undermine conclusions drawn from the model increases. Model verification, derived from the broader field of verification in software and hardware, offers a new way to tackle complexity. Here, mathematical proofs are used instead of simulation to analyze model behavior. These proofs can offer guarantees of model correctness that apply over all of state space, for example, stating that one gene is always activated transiently or another gene never becomes active. Examples include the computation of attractors [54] and proofs of stability [43], where proofs of properties of the whole model are composed of proofs computed on individual components.

Conclusion

The growing availability of high-quality, whole-cell biological data has underlined the need to develop rigorous integrative methods that connect observations to fundamental mechanisms of action. Data-driven model inference combined with high-quality biocuration could lead to the construction of more accurate and robust models. At the same time, the rapid adoption of increasingly large logic-based models stress tests the existing methods and tools used for dynamic analysis.

The key challenges of the field consist in developing efficient formalisms for data integration and tool implementations to properly combine and integrate data to models but also to analyze and understand these models at a larger scale. While model inference methodologies can greatly accelerate model building and training, the parallel development of formal methods for analysis, control, and verification is needed to cope with the size and complexity of such models. The coupling of logic-based models with other modeling types offers possibilities to address more complex questions spanning over different scales, such as signaling and metabolism. Lastly, the use of common annotation schemes and standard formats could help maximize transparency and model reusability and reproducibility (Figure 2).

Figure 2



Key challenges in integrating high-throughput data in logic-based models.

As multi-omics data will become increasingly available for a variety of biological functions in health and disease, logic-based models can be used as versatile, powerful tools to deepen our understanding of complex biological mechanisms.

Conflict of interest statement

Nothing declared.

Acknowledgements

The authors would like to thank Professor Denis Thieffry, IBENS, Paris, for the valuable comments and exchanges. AN is supported by an ANRT CIFRE contract (grant number 2020/0766). BAH is supported by a Royal Society University Research Fellowship (grant number UF130039).

References

Papers of particular interest, published within the period of review, have been highlighted as:

* of special interest
** of outstanding interest

1. Sugita M, Fukuda N: **Functional analysis of chemical systems in vivo using a logical circuit equivalent. 3. Analysis using a digital circuit combined with an analogue computer**. *J Theor Biol* 1963, **5**:412–425.

2. Kauffman SA: **Metabolic stability and epigenesis in randomly constructed genetic nets**. *J Theor Biol* 1969, **22**:437–467.

3. Thomas R: **Boolean formalisation of genetic control circuits**. *J Theor Biol* 1973, **42**:563–585.

4. Ostaszewski M, Gebel S, Kuperstein I, Mazein A, Zinovyev A, Dogrusoz U, Hasenauer J, Fleming RMT, Le Novère N, Gawron P, *et al.*: **Community-driven roadmap for integrated disease maps**. *Briefings Bioinf* 2019, **20**:659–670.

5. Wynn ML, Consul N, Merajver SD, Schnell S: **Logic-based models in systems biology: a predictive and parameter-free network analysis method**. *Integr Biol (Camb)* 2012, **4**: 1323–1337.

6. Abou-Jaoudé W, Traynard P, Monteiro PT, Saez-Rodriguez J, Helikar T, Thieffry D, Chaouiya C: **Logical modeling and dynamical analysis of cellular networks**. *Front Genet* 2016, **7**:94.

7. Niarakis A, Helikar T: **A practical guide to mechanistic systems modeling in biology using a logic-based approach**. *Briefings Bioinf* 2020, https://doi.org/10.1093/bib/bbaa236.

8. * Schwab JD, Kühlwein SD, Ikonomi N, Kühl M, Kestler HA: **Concepts in Boolean network modeling: what do they all mean?** *Comput Struct Biotechnol J* 2020, **18**:571–582.
Provides a comprehensive overview of all concepts used in Boolean modelling.

9. Suarez OJ, Vega CJ, Sanchez EN, González-Santiago AE, Rodríguez-Jorge O, Alanis AY, Chen G, Hernandez-Vargas EA: **Pinning control for the p53-mdm2 network dynamics regulated by p14ARF**. *Front Physiol* 2020, **11**:976.

10. Choi M, Shi J, Jung SH, Chen X, Cho K-H: **Attractor landscape analysis reveals feedback loops in the p53 network that control the cellular response to DNA damage**. *Sci Signal* 2012, **5**:ra83.

11. Proctor CJ, Gray DA: **Explaining oscillations and variability in the p53-Mdm2 system**. *BMC Syst Biol* 2008, **2**:75.

12. Niarakis A, Bounab Y, Grieco L, Roncagalli R, Hesse A-M, Garin J, Malissen B, Daëron M, Thieffry D: **Computational modeling of the main signaling pathways involved in mast cell activation**. *Curr Top Microbiol Immunol* 2014, **382**:69–93.

13. Bounab Y, Hesse A-M-, Iannascoli B, Grieco L, Couté Y, Niarakis A, Roncagalli R, Lie E, Lam K-P, Demangel C, *et al.*: **Proteomic analysis of the SH2 domain-containing leukocyte protein of 76 kDa (SLP76) interactome in resting and activated primary mast cells [corrected]**. *Mol Cell Proteomics* 2013, **12**:2874–2889.

14. Collombet S, van Oevelen C, Sardina Ortega JL, Abou-Jaoudé W, Di Stefano B, Thomas-Chollier M, Graf T, Thieffry D: **Logical modeling of lymphoid and myeloid cell specification and transdifferentiation**. *Proc Natl Acad Sci USA* 2017, **114**: 5792–5799.

15. Tsirvouli E, Touré V, Niederdorfer B, Vázquez M, Flobak Å, Kuiper M: **A middle-out modeling strategy to extend a colon cancer logical model improves drug synergy predictions in epithelial-derived cancer cell lines**. *Front. Mol. Biosci.* 2020, **7**:502573.

16. Guinney J, Dienstmann R, Wang X, de Reyniès A, Schlicker A, Soneson C, Marisa L, Roepman P, Nyamundanda G, Angelino P, *et al.*: **The consensus molecular subtypes of colorectal cancer**. *Nat Med* 2015, **21**:1350–1356.

17. * Niederdorfer B, Touré V, Vazquez M, Thommesen L, Kuiper M, Lægreid A, Flobak Å: **Strategies to enhance logic modeling-based cell line-specific drug synergy prediction**. *Front Physiol* 2020, **11**:862.

Describes the use of logic-based models to predict cell line-specific drug combination effects based on omic-inferred baseline calibration data.

18. Palma A, Jarrah AS, Tieri P, Cesareni G, Castiglione F: **Gene regulatory network modeling of macrophage differentiation corroborates the continuum hypothesis of polarisation states**. *Front Physiol* 2018, **9**:1659.

19. Marku M, Verstraete N, Raynal F, Madrid-Mencía M, Domagala M, Fournié J-J, Ysebaert L, Poupot M, Pancaldi V: **Insights on TAM formation from a boolean model of macrophage polarization based on in vitro studies**. *Cancers* 2020, **12**.

20. Cohen DPA, Martignetti L, Robine S, Barillot E, Zinovyev A, Calzone L: **Mathematical modelling of molecular pathways enabling tumour cell invasion and migration**. *PLoS Comput Biol* 2015, **11**, e1004571.

21. Riedel A, Shorthouse D, Haas L, Hall BA, Shields J: **Tumor-induced stromal reprogramming drives lymph node transformation**. *Nat Immunol* 2016, **17**:1118–1127.

22. Shorthouse D, Riedel A, Kerr E, Pedro L, Bihary D, Samarajiwa S, Martins CP, Shields J, Hall BA: **Exploring the role of stromal osmoregulation in cancer and disease using executable modelling**. *Nat Commun* 2018, **9**:3011.

23. Saez-Rodriguez J, Blüthgen N: **Personalised signaling models for personalised treatments**. *Mol Syst Biol* 2020, **16**, e9042.

24. Béal J, Montagud A, Traynard P, Barillot E, Calzone L: **Personalisation of logical models with multi-omics data allows clinical stratification of patients**. *Front Physiol* 2018, **9**:1965.

25. * Béal J, Pantolini L, Noël V, Barillot E, Calzone L: **Personalised logical models to investigate cancer response to BRAF treatments in melanomas and colorectal cancers**. *PLoS Comput Biol* 2021, **17**, e1007900.

Describes a comprehensive pipeline from clinical question to a validated mechanistic model that uses different omics data types and adapts to dozens of different cell lines.

26. Silverbush D, Grosskurth S, Wang D, Powell F, Gottgens B, Dry J, Fisher J: **Cell-specific computational modeling of the PIM pathway in acute myeloid leukemia**. *Canc Res* 2017, **77**: 827–838.

27. Palma A, Iannuccelli M, Rozzo I, Licata L, Perfetto L, Massacci G, Castagnoli L, Cesareni G, Sacco F: **Integrating patient-specific information into logic models of complex diseases: application to acute myeloid leukemia**. *J Personalized Med* 2021:11.

28. Razzaq M, Paulevé L, Siegel A, Saez-Rodriguez J, Bourdon J, Guziolowski C: **Computational discovery of dynamic cell line specific Boolean networks from multiplex time-course data**. *PLoS Comput Biol* 2018, **14**, e1006538.

29. Ostrowski M, Paulevé L, Schaub T, Siegel A, Guziolowski C: **Boolean network identification from perturbation time series data combining dynamics abstraction and logic programming**. *Biosystems* 2016, **149**:139–153.

30. Dorier J, Crespo I, Niknejad A, Liechti R, Ebeling M, Xenarios I: **Boolean regulatory network reconstruction using literature based knowledge with a genetic algorithm optimisation method**. *BMC Bioinf* 2016, **17**:410.

31. ** Gjerga E, Trairatphisan P, Gabor A, Koch H, Chevalier C, Ceccarelli F, Dugourd A, Mitsos A, Saez-Rodriguez J: **Converting networks to predictive logic models from perturbation signalling data with CellNOpt**. *Bioinformatics* 2020, **36**:4523–4524.

An updated collection of Bioconductor R packages for building logic-based models of signalling networks from perturbation data and prior knowledge to handle more efficiently large datasets.

32. Terfve C, Cokelaer T, Henriques D, MacNamara A, Goncalves E, Morris MK, van Iersel M, Lauffenburger DA, Saez-Rodriguez J: **CellNOptR: a flexible toolkit to train protein signaling networks to data using multiple logic formalisms**. *BMC Syst Biol* 2012, **6**:133.

33. Barman S, Kwon Y-K: **A Boolean network inference from time-series gene expression data using a genetic algorithm**. *Bioinformatics* 2018, **34**:i927–i933.

34. Palli R, Palshikar MG, Thakar J: **Executable pathway analysis using ensemble discrete-state modeling for large-scale data**. *PLoS Comput Biol* 2019, **15**, e1007317.

35. Moignard V, Woodhouse S, Haghverdi L, Lilly AJ, Tanaka Y, Wilkinson AC, Buettner F, Macaulay IC, Jawaid W, Diamanti E, Nishikawa SI, Piterman N, Kouskoff V, Theis FJ, Fisher J, Göttgens B: **Decoding the regulatory network of early blood development from single-cell gene expression measurements**. *Nat Biotechnol* 2015, **33**:269–276.

36. Lim CY, Wang H, Woodhouse S, Piterman N, Wernisch L, Fisher J, Göttgens B: **BTR: training asynchronous Boolean models using single-cell expression data**. *BMC Bioinf* 2016, **17**:355.

37. ** Aghamiri SS, Singh V, Naldi A, Helikar T, Soliman S, Niarakis A: **Automated inference of Boolean models from molecular interaction maps using CaSQ**. *Bioinformatics* 2020, **36**: 4473–4482.

Describes a "map-to-model framework" using CaSQ, a software tool that infers Boolean rules based on the topology and semantics of molecular interaction maps, creating annotated, fully executable large-scale Boolean networks.

38. Chaouiya C, Naldi A, Thieffry D: **Logical modelling of gene regulatory networks with GINsim**. *Methods Mol Biol* 2012, **804**: 463–479.

39. Helikar T, Kowal B, McClenathan S, Bruckner M, Rowley T, Madrahimov A, Wicks B, Shrestha M, Limbu K, Rogers JA: **The Cell Collective: toward an open and collaborative approach to systems biology**. *BMC Syst Biol* 2012, **6**:96.

40. Müssel C, Hopfensitz M, Kestler HA: **BoolNet–an R package for generation, reconstruction, and analysis of Boolean networks**. *Bioinformatics* 2010, **26**:1378–1380.

41. ** Hall BA, Fisher J: **Constructing and analysing computational models of cell signaling with BioModelAnalyzer**. *Curr. Protoc. Bioinformatics* 2020, **69**:e95.

Describes a comprehensive protocol to construct and analyse large-scale Boolean models with BMA.

42. Paterson YZ, Shorthouse D, Pleijzier MW, Piterman N, Bendtsen C, Hall BA, Fisher J: **A toolbox for discrete modelling of cell signalling dynamics**. *Integr Biol (Camb)* 2018, **10**: 370–382.

43. Cook B, Fisher J, Krepska E, Piterman N: **Proving stabilization of biological systems**. In Jhala R, Schmidt D. *Verification, model checking, and abstract interpretation. VMCAI. Lecture Notes in computer science*, vol. 6538; 2011:134–149.

44. Cook B, Fisher J, Hall BA, Ishtiaq S, Juniwal G, Piterman N: **Finding instability in biological models**. In Biere A, Bloem R. *Computer aided verification. CAV 2014. Lecture notes in computer* science, vol. 8559; 2014:358–372.

45. Claessen K, Fisher J, Ishtiaq S, Piterman N, Wang Q: **Model-checking signal transduction networks through decreasing reachability sets**. In Sharygina N, Veith H. *Computer aided verification. CAV 2013. Lecture notes in computer science 2013*, vol. 8044; 2013:85–100.

46. Marmiesse L, Peyraud R, Cottret L: **FlexFlux: combining metabolic flux and regulatory network analyses**. *BMC Syst Biol* 2015, **9**:93.

47. * van der Zee L, Barberis M: **Advanced modeling of cellular proliferation: toward a multi-scale framework coupling cell cycle to metabolism by integrating logical and constraint-based models**. *Methods Mol Biol* 2019, **2049**:365–385.

Describes a computational, multi-scale framework that couples off-the-shelf logical (Boolean) models of the yeast cell cycle with a constraint-based model of metabolism.

48. Tiwari K, Kananathan S, Roberts MG, Meyer JP, Sharif Shohan MU, Xavier A, Maire M, Zyoud A, Men J, Ng S, *et al.*: **Reproducibility in systems biology modelling**. *Mol Syst Biol* 2021, **17**, e9982.

49. * Niarakis A, Kuiper M, Ostaszewski M, Malik Sheriff RS, Casals-Casas C, Thieffry D, Freeman TC, Thomas P, Touré V, Noël V, *et al.*: **Setting the basis of best practices and standards for curation and annotation of logical models in biology-highlights of the [BC]2 2019 CoLoMoTo/SysMod Workshop. Brief**. *Bioinformatics* 2021, **22**:1848–1859.

Roadmap for the building of interoperable, reusable, and reproducible logic-based models

50. Chaouiya C, Bérenguier D, Keating SM, Naldi A, van Iersel MP, Rodriguez N, Dräger A, Büchel F, Cokelaer T, Kowal B, *et al.*: **SBML qualitative models: a model representation format and infrastructure to foster interactions between qualitative modelling formalisms and tools**. *BMC Syst Biol* 2013, **7**:135.

51. Naldi A, Hernandez C, Levy N, Stoll G, Monteiro PT, Chaouiya C, Helikar T, Zinovyev A, Calzone L, Cohen-Boulakia S, *et al.*: **The colomoto interactive notebook: accessible and reproducible computational analyses for qualitative biological networks**. *Front Physiol* 2018, **9**:680.

52. ** Paulevé L, Kolčák J, Chatain T, Haar S: **Reconciling qualitative, abstract, and scalable modeling of biological networks**. *Nat Commun* 2020, **11**:4256.

Describes the most permissive Boolean networks (MPBNs) that provides a formal guarantee not to miss dynamic behaviours observable in quantitative models following the same logic. MPBNs can reduce the complexity of dynamical analysis, enabling the modelling of large-scale networks.

53. Baudin A, Paul S, Su C, Pang J: **Controlling large Boolean networks with single-step perturbations**. *Bioinformatics* 2019, **35**:i558–i567.

54. * Hernandez C, Thomas-Chollier M, Naldi A, Thieffry D: **Computational verification of large logical models-application to the prediction of T cell response to checkpoint inhibitors**. *Front Physiol* 2020, **11**:558606.

Describes two approaches to cope with analysing complex, large-scale logic-based models. Local model verification is inspired by unit testing, and input propagation helps to assess the impact of constraints on the dynamical behaviour.