

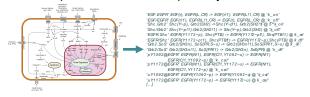
Logical Inference for Rule-Based Biological Models



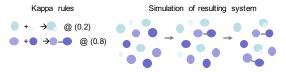
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Goal: executable models

- Executable models help researchers examine systems and develop hypotheses.
- Example: models of cancer pathways.

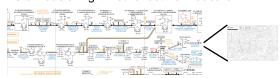


- Such models have applications in personalized medicine, drug design, and basic research.
- Kappa is a language used to program and run rulebased biological models, with one rule per reaction.



Automatic model generation

- Biological knowledge is immense, complex, and always changing.
- Old models might not reflect new research.



 Researchers are working to fix this by generating rule-based models from NLP on research papers.

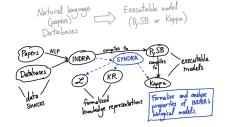
The problem

- Statements produced by NLP may be ambiguous or incomplete.
- We want to analyze these statements, and perform logical queries over them to detect issues.



Contributions

- Developed approach for integrating semantic and chemical reasoning.
- Implemented tool, Syndra, using Python and Z3.
- Demonstrated feasibility of tool in resolving logical inferences on small real-world examples.
- Integrated tool with model generation framework, including NLP frontend.



How it works

- Translate NLP statements into predicates.
- Predicates constrain the space of possible models.



· Can perform logical queries over this space.

A logic for biological models

- Implemented Iota, a logic language designed to describe valid Kappa programs. [Husson & Krivine]
- Example: predicate "phosphorylated A binds to B" –

 $PreLabeled(A, phosphorylated) \land PreUnbound(A, B)$ $\land PostLabeled(A, phosphorylated) \land PostBound(A, B)$

- A model is a set of reaction rules; each reaction rule is described formally by transformations on a graph.
- A predicate specifies each graph transformation by preconditions and postconditions on the graph state.

Implementing the logic

- Defined Z3 datatypes for lota components.
- · Implemented each logical operator of lota.

Results

Functionality

Supports the following user-facing functionality:

- Check satisfiability of any predicate.
- Construct a model satisfying a predicate.
- Check implication between two predicates.

Proving implications

- Define *macros* for commonly-used predicates, formally defining what rules mean.
- Can prove that two rules imply another statement. Consider the example:

```
Rules
1. Protein A phosphorylates protein B.
2. When phosphorylated, protein B is active.
3. Protein A activates protein B.

Question: do 1 and 2 necessarily imply 3? Yes, we can prove that they do!

>>> p1 = macros.directly_phosphorylates("A", "B")

>>> p2 = macros.phosphorylated_is_active("B")

>>> p3 = macros.directly_activates("A", "B")

>>> predicate.And(p1, p2).check_implies(p3)
True
```

 This allows us to prove inference rules correct in terms of the underlying chemistry of each rule.

Interfacing with an NLP model-generator

- INDRA is a tool which generates Kappa models from NI P.
- Can convert INDRA statements into iota predicates, and perform queries over those predicates.
- Example: can detect that **s4** is redundant!

```
statements...
s1 = Phosphorylation(MAP2K1, MAPK1, PhosphorylationThreonine, 183)
s2 = Phosphorylation(MAP2K1, MAPK1, PhosphorylationTyrosine, 185)
s3 = ActivityModification(MAPK1, ['PhosphorylationThreonine', 'PhosphorylationTyrosine'], ['183', '185'], increases, Activity)
s4 = ActivityActivity(MAP2K1, Kinase, increases, MAPK1, Kinase)
...converted to Syndra predicates
>>> pred = syndra_from_statements(s1, s2, s3)
>>> pred.check_sat()
True
>>> pred.check_implies(syndra_from_statements(s4)
True
```