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Formal modeling of Gene Ontology annotation predictions based on factor graphs

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Abstract.

Gene Ontology (GO) is a hierarchical vocabulary for gene product annotation. Its synergy with machine learning classification methods has been widely used for the prediction of protein functions. Current classification methods rely on heuristic solutions to check the consistency with some aspects of the underlying GO structure. In this work we formalize the GO *is-a* relationship through predicate logic. Moreover, an ontology model based on Forney Factor Graph (FFG) is shown on a general fragment of Cellular Component GO.

1. Introduction

The high-throughput sequencing technologies entail new challenges in data processing. As a result, the use of machine learning algorithms has become relevant in many bioinformatics applications [1, 2]. In particular, for Automated Functional protein Prediction (AFP) based on Gene Ontology (GO), ensemble methods consider the ontological structure (DAG, directed acyclic graph) through a hierarchical classification [3, 4]. The design of ensemble methods is made in two steps: *i*) In the first one, a set of binary classifiers is built to predict GO-terms (classes), *ii*) In the second one, consistency of GO-DAG relationship is done. Focusing on this last step, different solutions based on heuristics [5, 6] have been proposed such as the True Path Rule (TPR) algorithm [5] where the *is-a* DAG relationship is fulfilled implementing the rule: “If the child term describes the gene product, then all its parent terms must also apply to that gene product”.

Heuristic solutions may be a good accuracy-effort trade-off, but a step beyond to attempt logical formalization for checking the DAG restrictions. In this paper we propose that formalization through Forney Factor Graph (FFG) model [7], since it allows a TPR restriction representation by the logical factorization of functions of several variables associated with GO-terms. The achieved model, called FFG-GO, is able to infer functional predictions of genes by using the sum-product algorithm [8].

In the next Section a brief background of FFG is presented. Then, in Section 3 TPR restrictions are formalized through predicate logic, in Section 4 FFG-GO model is described. In the last Section, a subgraph of Cellular Component GO is modeled by FFG-GO.



2. Background

An FFG is a model that represents the factorization of a function for several variables. Briefly, the FFG diagram (Fig. 1) has nodes, ordinary edges, and leaf-edges interpreted as follows: each factor f_i (also called function) is represented by a *node*; each state variable S_j is between two factors and is represented by an *ordinary-edge*; and each input variable A_k must be involved in just one factor and represented by a *leaf-edge*. The global function (f) is factorized into factors as a product of local functions, where each factor depends on a subset of variables of f . For instance, the function $f(A_1, A_2, A_3, A_4, S_1, S_2, S_3)$ can be factorized as:

$$f(A_1, A_2, A_3, A_4, S_1, S_2, S_3) = f_1(A_1, S_1)f_2(A_2, S_1, S_2, S_3)f_3(A_3, S_2)f_4(A_4, S_3) \quad (1)$$

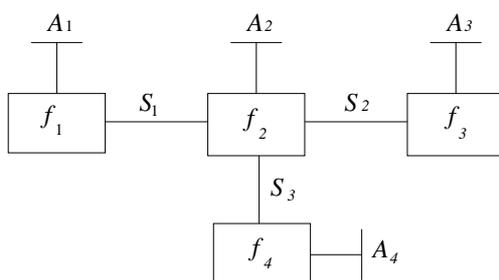


Figure 1: FFG diagram. Boxes are factors, f_i their functions; ordinary-edges, S_j their state variables; and leaf-edges, A_k their input variables.

3. Formalizing GO and TPR restrictions

Aiming to include the GO constraint into FFG model, the TPR restriction is formulated by predicate logic. Next, GO-DAG is denoted by $G = (V, \leq)$, where V is a set of GO terms and \leq is a binary relation on V . GO terms are represented by GO nodes (GO_1, \dots, GO_m) where m is the cardinality of V . $GO_l \leq GO_z$ denotes that GO_z is a parent of GO_l , written in predicate logic as $is_a(GO_l, GO_z)$.

The Gene Ontology Consortium has defined the TPR restriction to guarantee the is_a GO-DAG consistency as follows: “An annotation for a class in the hierarchy is automatically transferred to its ancestors, while unannotated genes for a class cannot be annotated for its descendants”. Note that classes are GO terms and annotation is the process of assigning GO terms to gene products.

Based on [9], we rewrite the TPR by two rules of predicate logic: one related to the parents (Eq.2) and the other related to offspring (Eq.3).

$$r_1 : \forall GO_k \left(is_a(GO_l, GO_k) \wedge pos(GO_l) \rightarrow pos(GO_k) \right) \quad (2)$$

$$r_2 : \forall GO_k \left(is_a(GO_k, GO_z) \wedge \neg pos(GO_z) \rightarrow \neg pos(GO_k) \right) \quad (3)$$

where $pos(GO_k)$ means a gene annotation with the GO_k term.

4. FFG-GO model

Regarding the GO behavior modeling under FFG, some GO issues are briefly recalled. The gene ontology is composed of nodes representing gene functions, i.e., the k -th node and its function are jointly called $GO:k$. The GO nodes are connected in a DAG structure through edges that

characterize node relationships. Without losing generality, in this work we focus on *is-a* relation. In Fig. 2(a) a comprehensive GO example that considers multiple offspring-parents is illustrated, while Fig. 2(b) shows its FFG-GO counterpart. GO nodes are matched to FFG model by input variables for root and leaves nodes, and by input state variables for inner nodes. For instance, the leaf *GO:5* matches to A_5 , and the inner node *GO:2* matches to A_2 , S_1 , and S_2 . The DAG relationships together with GO restrictions are represented by FFG functions that depend on state and input variables. For instance, r_{12} and r_{13} relation match to the function f_1 .

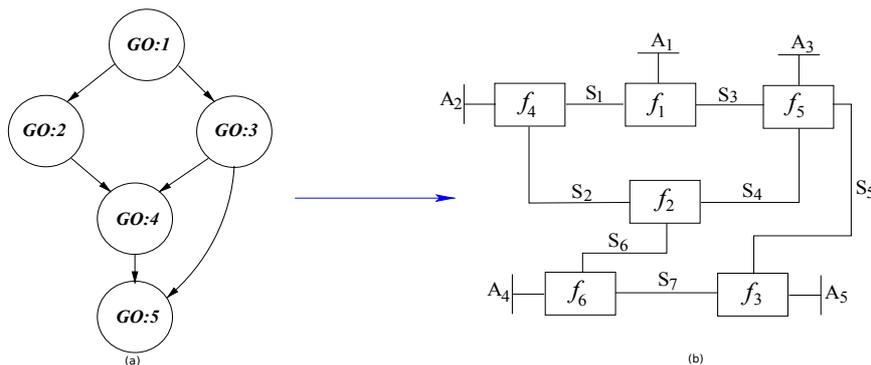


Figure 2: (a). The GO-DAG example. (b). The FFG-GO counterpart. $GO:k$ node is translated to A_k/S_j variables, GO relationship r are $f_i(S_j, A_k)$.

The strength of FFG model is the design of functions f_i through logical expressions [10] to describe both the native FFG constraints and the GO-DAG restrictions. In the FFG-GO approach we identify three kinds of factors: *equality*, *multiple offspring*, and *multiple inheritance*. Note that the equality is a native FFG factor, but the inclusion of the multiple offspring together with multiple inheritances allows the formal implementation of TPR.

Equality constraint: Also called identity function and symbolized with $f_=_$ forces all its variables to be equals. It is required in the FFG building [7, 11]. Fig. 3 shows the identify function block, Table 1 describes its truth table, where as expected $f_=_ = 1$ when all its variables (A_2, S_1, S_2) are equals.

Table 1: Truth table for equality constraint.
Inputs: A_2, S_1 and S_2 ; Output: $f_=_$

A_2	S_1	S_2	$f_=(A_2, S_1, S_2)$
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	0
1	0	0	0
1	0	1	0
1	1	0	0
1	1	1	1

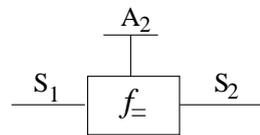


Figure 3: Identity function in graphic FFG-GO model

The $f_=_$ Boolean expression is $f_=(A_2, S_1, S_2) = A_2 \cdot S_1 \cdot S_2 + \overline{A_2} \cdot \overline{S_1} \cdot \overline{S_2}$

The general form for equality constraint is:

$$f_{=} (A_k, S_1, \dots, S_n) = \begin{cases} 1 & \text{pos}(A_k) \wedge \text{pos}(S_1) \wedge \dots \wedge \text{pos}(S_j) \vee \neg \text{pos}(A_k) \wedge \neg \text{pos}(S_1) \wedge \dots \wedge \neg \text{pos}(S_j) \quad j = 1, \dots, n \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Multiple offspring: Symbolized with f_{\wedge} , it describes the allowed node states depending on its multiple children states. See Fig. 4 where $GO:1$ matches to A_1 , $GO:2$ to A_2 and S_1 , and $GO:3$ to A_3 and S_3 ; Table 2 describes its truth table according to the predicate logic of Eq. 3.

Table 2: Truth table for multiple offspring. Inputs: A_2 , S_1 and S_3 ; Output: f_{\wedge}

A_1	S_1	S_3	$f_{\wedge}(A_1, S_1, S_3)$
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	0
1	0	0	1
1	0	1	1
1	1	0	1
1	1	1	1

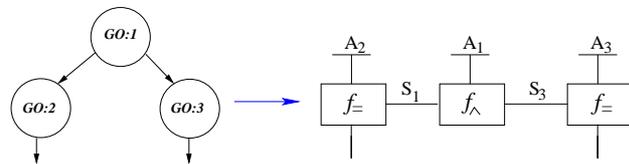


Figure 4: Multiple offspring in FFG-GO graphic model.

The f_{\wedge} Boolean expression is $f_{\wedge}(A_1, S_1, S_3) = A_1 + \overline{A_1} \cdot \overline{S_1} \cdot \overline{S_3}$

The general form for multiple offspring constraint is:

$$f_{\wedge}(A_k, S_1, \dots, S_n) = \begin{cases} 1 & \text{pos}(A_k) \vee \neg \text{pos}(A_k) \wedge \neg \text{pos}(S_1) \wedge \dots \wedge \neg \text{pos}(S_j) \quad j = 1, \dots, n \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The A_k is the FFG input variable that represents the parent GO node, and S_1 to S_n are variables that represent its children.

Multiple inheritance: Symbolized with f_{\vee} , it describes the allowed node states depending on its multiple parent states. See Fig. 5 where $GO:4$ matches to A_4 and S_6 , $GO:2$ to A_2 and S_2 , and $GO:3$ to A_3 and S_4 ; Table 3 describes its truth table according to the predicate logic of Eq. 2.

Table 3: Truth table for multiple inheritance. Inputs: S_6, S_2 and S_4 ; Output: f_v

S_6	S_2	S_4	$f_v(S_6, S_2, S_4)$
0	0	0	1
0	0	1	1
0	1	0	1
0	1	1	1
1	0	0	0
1	0	1	0
1	1	0	0
1	1	1	1

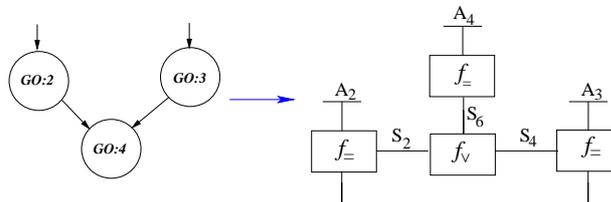


Figure 5: Multiple inheritance in FFG-GO graphic model.

The f_v Boolean expression is $f_v(S_6, S_2, S_4) = \overline{S_6} + S_6 \cdot S_2 \cdot S_4$

The general form for multiple inheritance constraint is as follow:

$$f_v(A_k, S_1, \dots, S_n) = \begin{cases} 1 & \neg pos(A_k) \vee pos(A_k) \wedge pos(S_1) \wedge \dots \wedge pos(S_j) \quad j = 1, \dots, n \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The S_1 to S_n are the variables that represents the parent GO nodes, and A_k is the input variable that represent its son.

Summarizing the GO to FFG-GO matching of the multiple offspring-inheritance example, Fig. 2, is shown in Fig. 6.

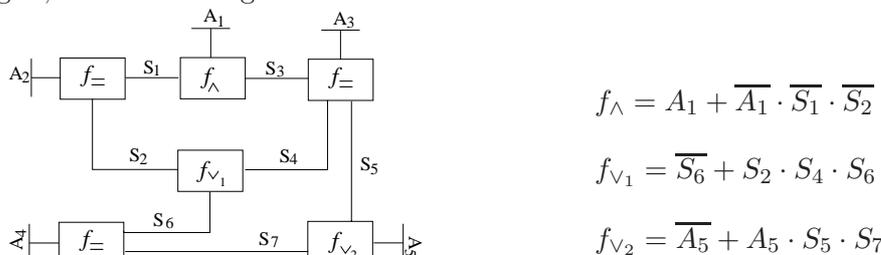


Figure 6: FFG-GO graphic model of multiple-offspring/inheritance, Fig. 2.

5. Results and discussion

In order to show the strength of the proposed FFG-GO, a model on a rich fragment of GO Cellular Component (CC) is done. This CC subgraph has all the TPR restrictions discussed above, see Fig. 7. For simplicity we have renamed GO nodes, $GO:1$ is the CC root $GO:0005575$, and $GO:2, \dots, GO:13$ are $GO:0032991, GO:0043226, GO:0043228, GO:0005623, GO:0032993, GO:0043229, GO:0044464, GO:0043232, GO:0032993, GO:0044426, GO:0044422, GO:0044427, GO:0030894$ respectively.

Fig. 8 shows FFG-GO model associated with CC fragment in Fig. 7. The f shows that the GO CC and FFG-GO matching, i.e., GO-terms match directly to A_k input variable. In one hand, the CC root $GO:1$ matches to A_1 input variable, and has always associated with the multiple offspring function f_\wedge . On the other hand, leaves ($GO:9, GO:13$) match to A_9, A_{13} input variables, and have always associated with the multiple inheritance function f_v . We should note

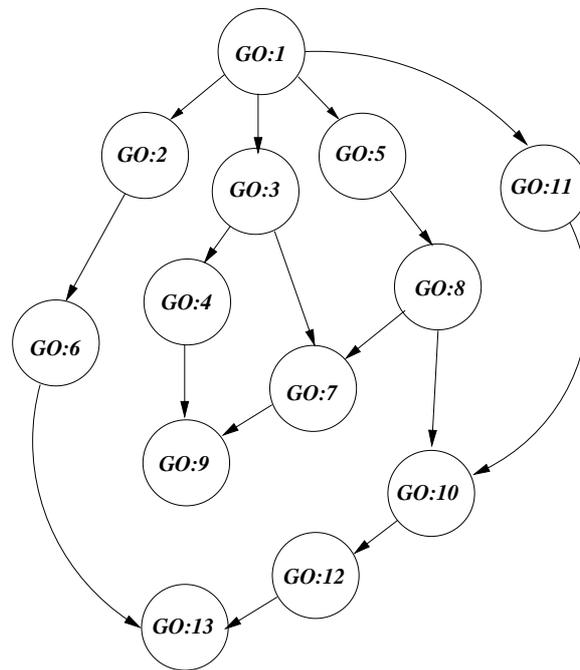


Figure 7: Cellular Component subgraph

that TPR restrictions are associated just with FFG-GO functions, hence, a restriction change requires a function modification but not a FFG-GO model rebuilding as happens with other approaches.

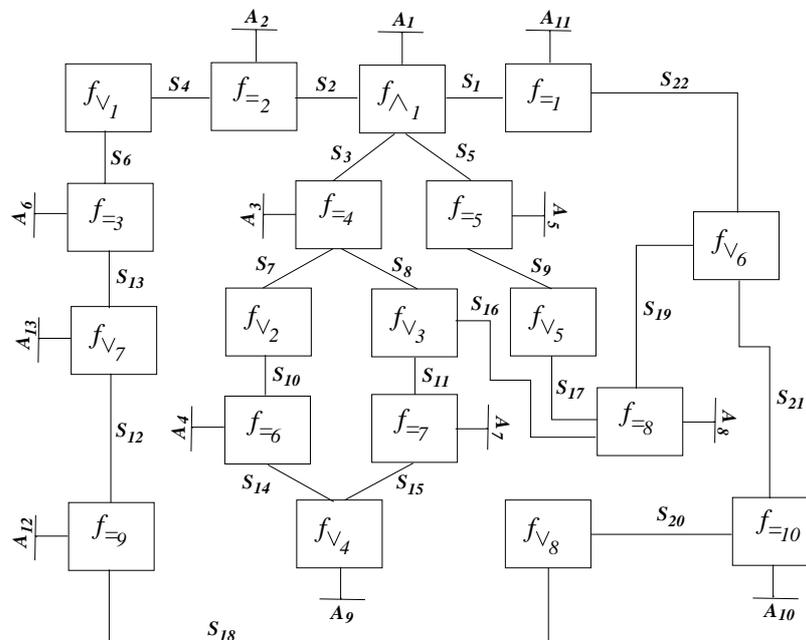


Figure 8: Cellular Component ontology in FFG-GO

The proposed FFG-GO model allows the formalization of *is-a* DAG relationship of GO ontology. Without loss of generality, the inclusion of new DAG relationships or restrictions

requires just a redesign of functions f without changing the core of FFG-GO model. Likewise, the insertion of new GO-terms is simple and easy to interpret graphically. In order to complete the GO-term annotation prediction for each sample (protein), a dynamic inference process must take place on the FFG-GO model. This inference process is carried out by the sum-product algorithm, but its description is out of the scope of this work, see [8] for details.

6. Conclusion

In ensemble classification methods, GO-term predictions computed by base binary classifiers are leveraged by checking the consistency of predefined GO relationships. Both formal leveraging strategies, with main focus on annotation precision, and heuristic alternatives, with main focus on scalability issues, have been described in literature.

Focusing on formal strategies, the formalization of TPR restrictions by predicate logic. The further work is to embody this formalization in a hierarchical classification method based on graphical models.

Along this paper we have focused our attention on *is_a* relationship of GO. However, this approach may be extended to another types of transitive relationships, such as *part of*, *has part*.

Acknowledgments

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