

Modeling Clinical Practice Guidelines using Predicate Logic for Reasoning with Incomplete Patient's Data

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Outline

- Clinical practice guidelines
- Executable guideline model
- Guideline as a decision and implication graph
- Reasoning from a guideline
- Discussion

Clinical Practice Guidelines (CPGs)

- Motivation for the CPG development and use: medical errors (IOM Study, 2001); need to practice evidence-based medicine; improve patient outcomes; control costs
- CPG: “systematically developed statements to assist practitioner and patient decisions about appropriate health care for specific clinical circumstances”
- “Our” CPG: “set of decision steps of varying level of abstraction and detail for diagnosis and/or management of patients who have specific clinical condition”

CPG Research

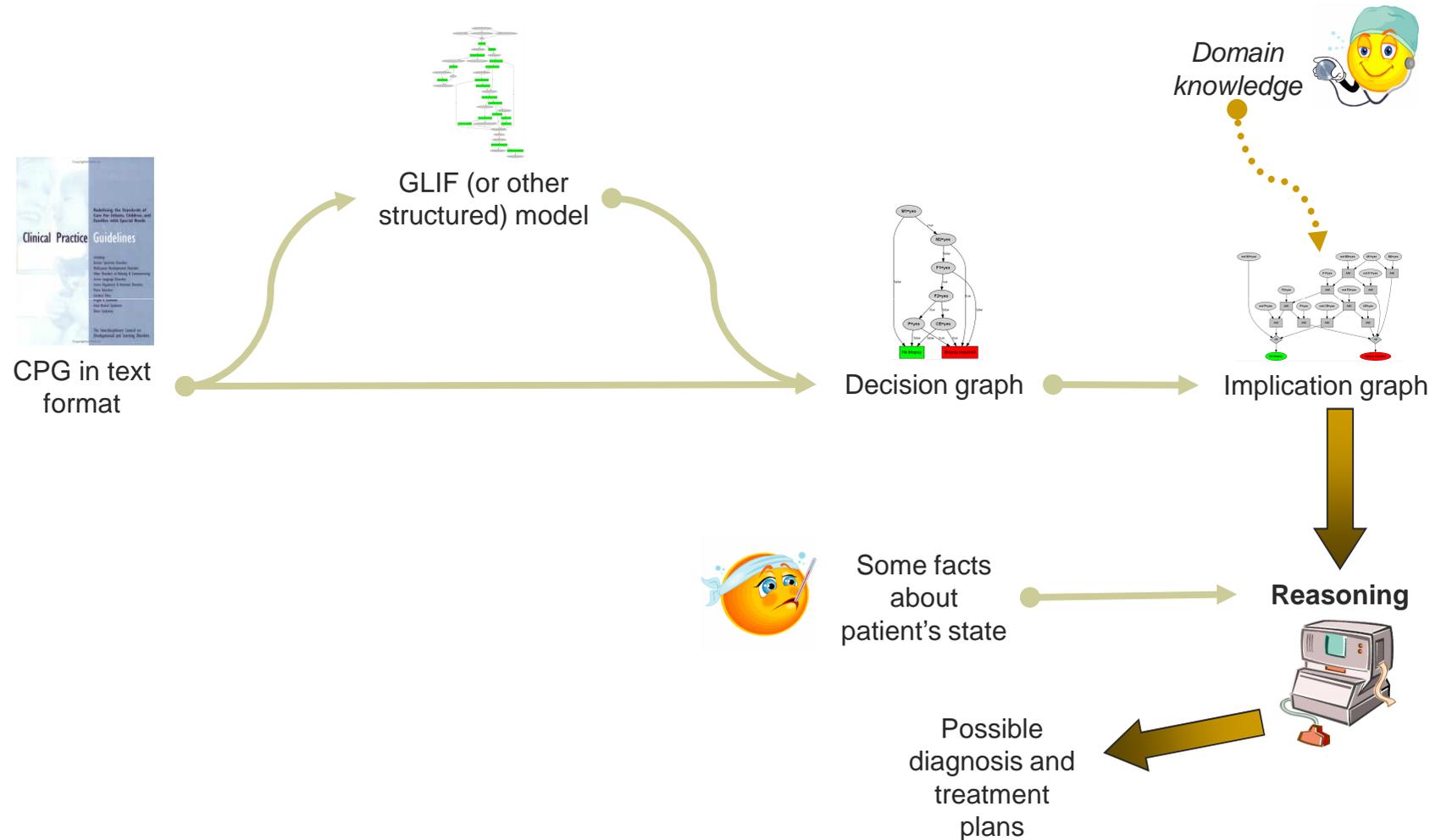
- Some examples of CPG models/formalisms:
 1. *Arden syntax*: Medical Logic Modules that include set of logical expressions implemented as production rules; has no execution standards
 2. *GLIF*: a flowchart translated into object-oriented model; GLEE execution engine under development
 3. *PROforma*: knowledge composition language for expert system-like use where CPG is modeled as a plan consisting of tasks; execution using Prolog-like interpreter
 4. *Asbru*: time-oriented CPG representation as a set of skeletal plans; executed mostly as a visualization tool

Gaps in Existing CPG Research

- Most of the attention has been paid to representing CPGs as models rather than implementing them clinically
- Implementation issues include:
 - How to customize CPG to local practice?
 - How to use CPG with missing or uncertain data?
 - How to integrate CPG with a decision support function?
 - How to adjust CPG to different levels of decision making expertise?

Our research question: How to use CPG with missing data

Proposed Approach: Enhance CPG Execution with Reasoning



Breast Mass (BM) CPG (1)

- Helps to decide whether a patient needs biopsy when breast mass was found (M. Borten. Breast Mass. In: Gynecological Decision Making, 1998)
- Possible outcomes:
 - biopsy required (to confirm or rule out malignant tumor)
 - no biopsy

Representing BM CPG in GLIF

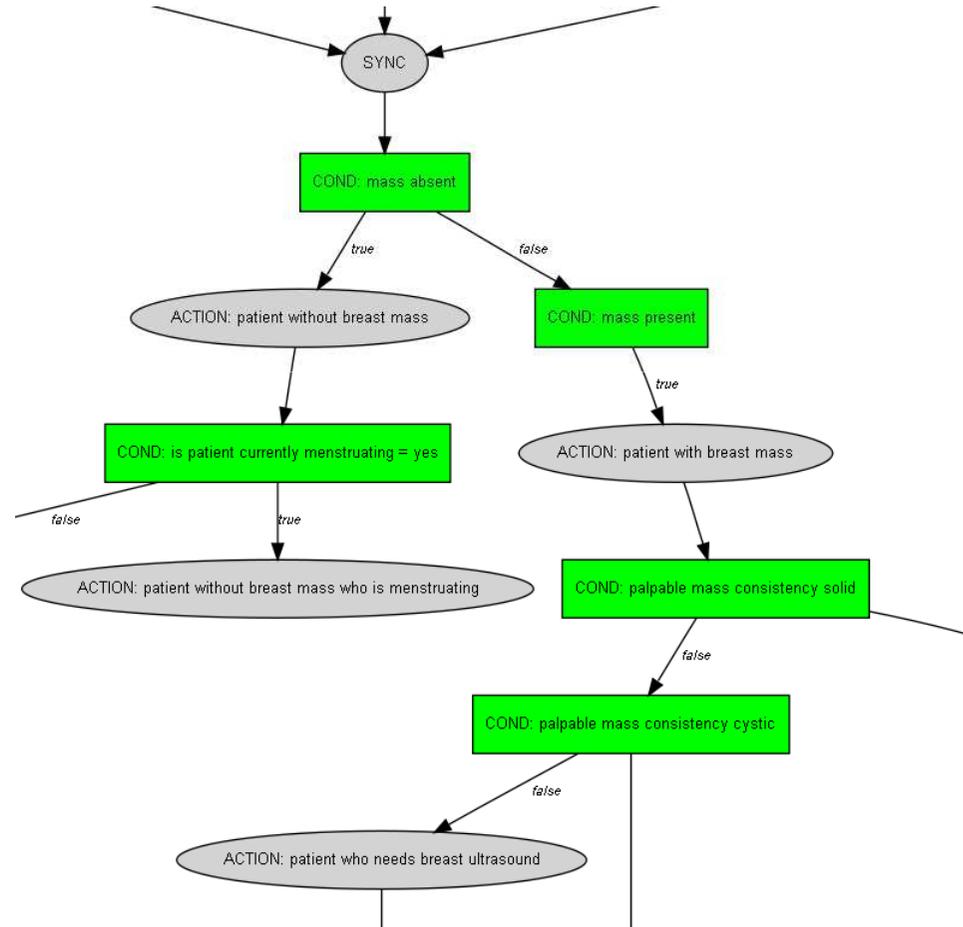
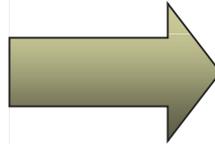
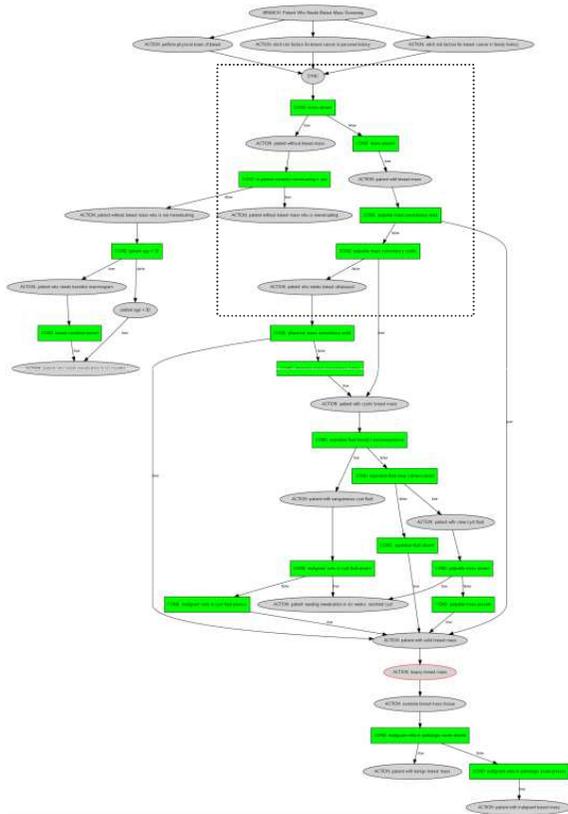
- Specification for structured representation of CPGs
 - Decision (conditional) step: palpable mass is cystic
 - Action step: aspirate cyst
 - Patient state step: patient requires biopsy
 - Branch and synchronization steps: sequencing
- Developed by the InterMed Collaboratory (Harvard, Stanford, Columbia, McGill) to facilitate sharing of CPGs
- Current specification – GLIF 3.5 (May 2004)

GLIF Model for BM CPG (1)

```
Guideline the_breast_mass_guideline
{
  name = "Breast Mass Guideline";
  authors = SEQUENCE 1 {"Max Borten, MD, JD"};
  eligibility_criteria = NULL;
  intention = "Evaluation of breast mass.";
  steps =
    SEQUENCE 40
    {
      (Branch_Step 1);
      (Action_Step 101);
      (Action_Step 102);
      (Action_Step 103);
      (Synchronization_Step 1031);
      (Conditional_Step 104);
      (Conditional_Step 105);
      (Action_Step 2);
      ...
    };
  first_step = (Branch_Step 1);
  didactics =
    SEQUENCE 1
    {
      Supplemental_Material 0.1
      {
        label = "critique";
        MIME_type = "text/plain";
        material = "Published guideline does not contain
explicit eligibility criteria.";
      };
    };
}
```

```
...
Action_Step 5
{
  name = "PATIENT WHO NEEDS REEVALUATION IN SIX MONTHS";
  action =
    Action_Spec 5.1
    {
      name = "Schedule Appointment, current date + 6 months";
      patient_data = SEQUENCE 0 {};
      description =
        "Schedule Appointment * {date = (current date + 6 months)}";
      didactics = SEQUENCE 0 {};
      subguideline = NULL;
      next_step = NULL;
      didactics = SEQUENCE 0 {};
    }
  ...
Conditional_Step 1001
{
  name = "";
  condition =
    Boolean_Criterion 10.1
    {
      type = k_three_valued;
      spec =
        "Breast_Palpation_Findings *
        {
          subject = Mass;
          presence = Absent;
        }";
      didactics = SEQUENCE 0 {};
    };
  destination = (Action_Step 11);
  otherwise = (Conditional_Step 1002);
  didactics = SEQUENCE 0 {};
}
```

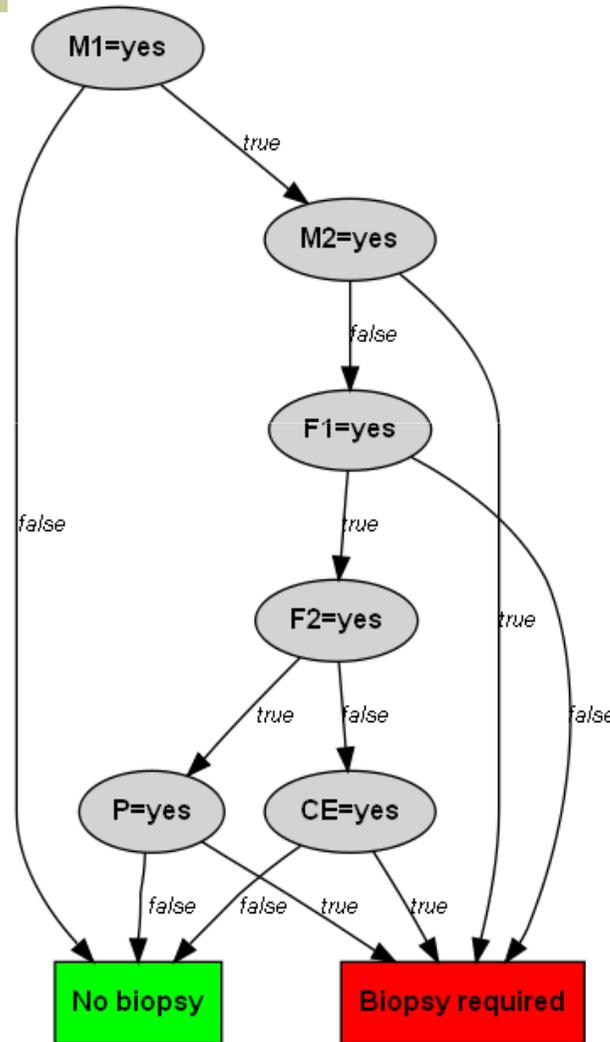
GLIF Model for BM CPG (2)



Decision Graph

- Created from the GLIF model (or other structured representation), but can be also developed from natural language CPG (expert knowledge required)
- Limited to decision and patient state steps (focus on clinical decision making)

Decision Graph for BM CPG



<i>M1</i>	Found breast mass
<i>M2</i>	Solid breast mass
<i>F1</i>	Fluid aspirated from cyst
<i>F2</i>	Clear aspirated fluid
<i>P</i>	Palpable breast mass
<i>CE</i>	Positive cytologic examination

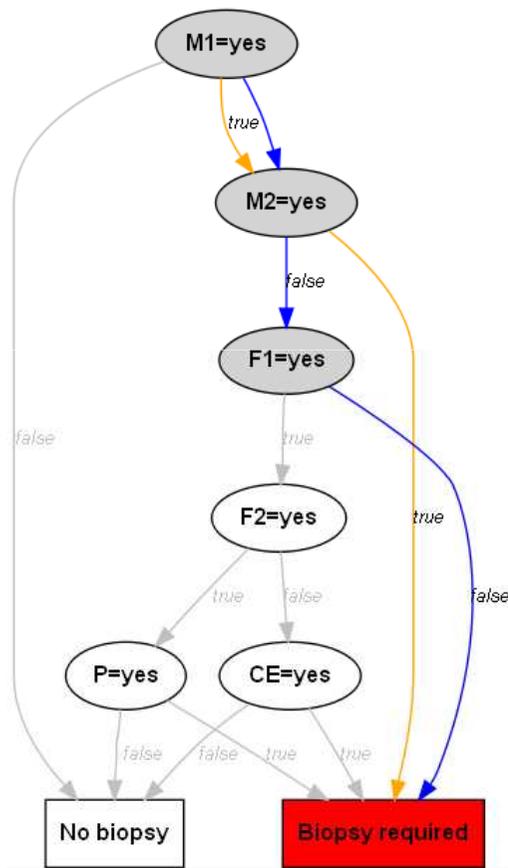
Implication Graph

- Inspired by implication trees used in legal reasoning (V. Walker, Visualizing the Dynamics around the Rule/Evidence Interface in Legal Reasoning, *Law, Probability and Risk* 6, 2007, 5-22)
- Based on the decision graph (→ inverted structure)
- Labeled arcs from the decision graph become nodes in the implication graph
- Additional nodes corresponding to conjunction and disjunction

From Decision to Implication Graph

- Step 1: Represent all paths in the decision graph as decision rules (*if conditions, then outcome*)
- Step 2: In the rules identify nodes of the implication graph
 - Fact and outcome nodes
 - Logical operator nodes (operator nodes in short)
- Step 3: In the rules identify arcs of the implication graph
 - Fact nodes connected to operator nodes
 - Operator nodes connected to other operator nodes and to outcome nodes

Step 1: Represent all paths as decision rules



- Decision rules corresponding to two sample paths

- $([M1=yes] = true)$
AND $([M2=yes] = true)$
→ Biopsy required
- $([M1=yes] = true)$
AND $([M2 = yes] = false)$
AND $([F1 = yes] = false)$
→ Biopsy required

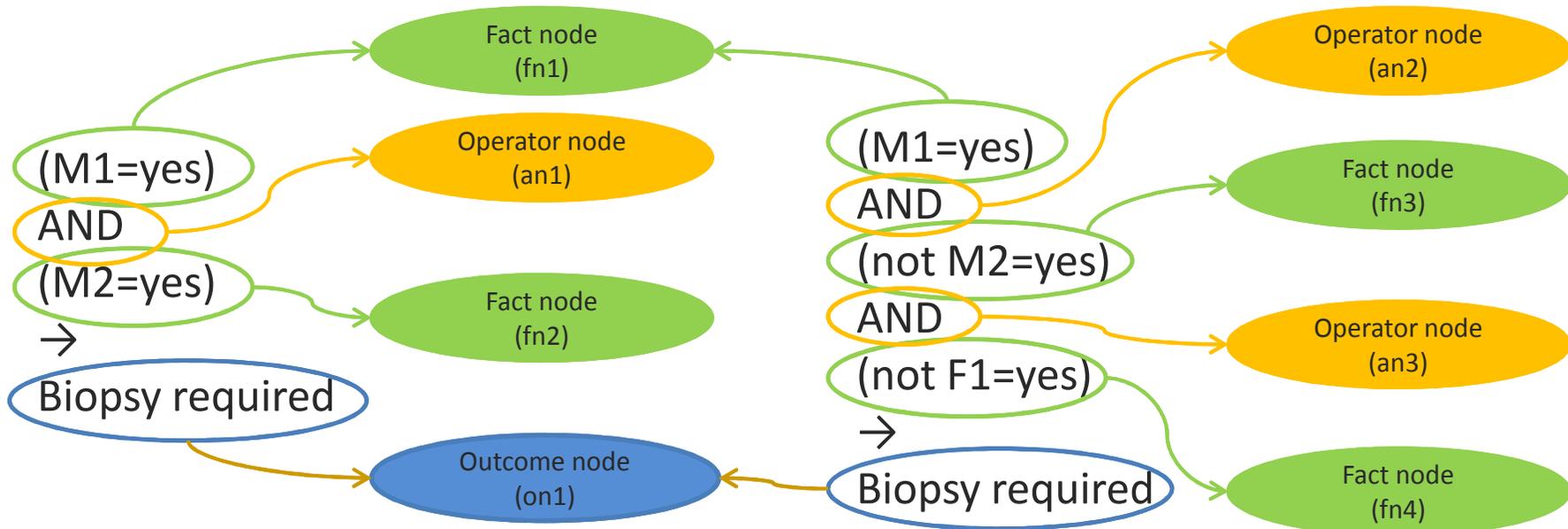
Simplified notation

$([A=yes] = true) \rightarrow (A=yes)$

$([A=yes] = false) \rightarrow (\text{not } A=yes)$

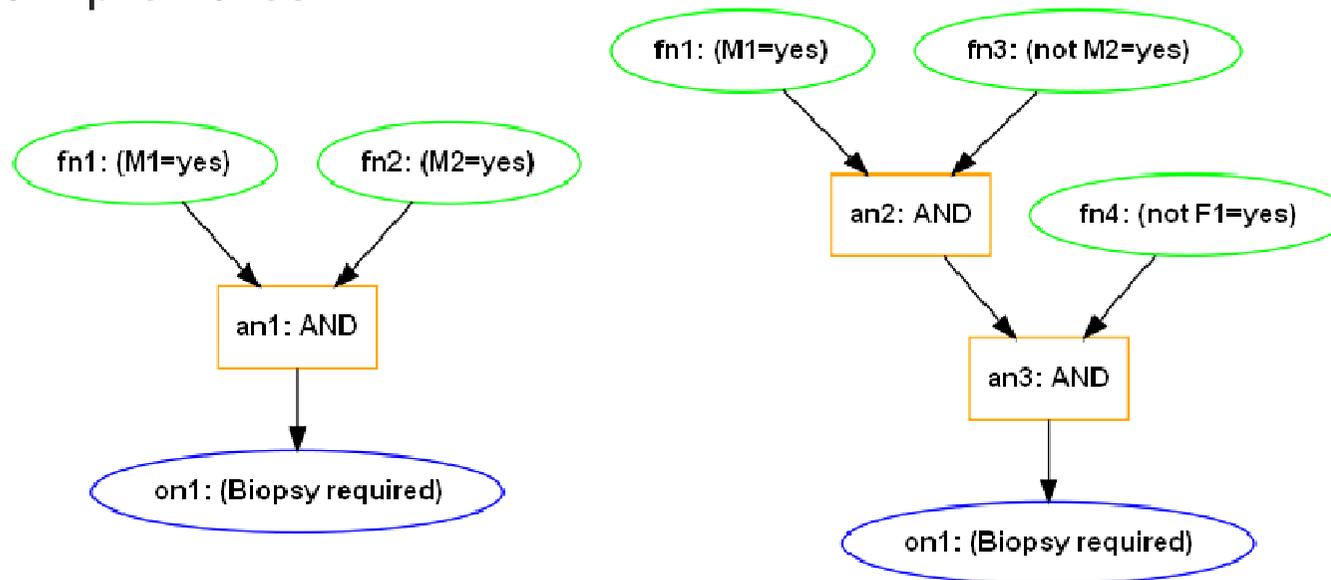
Step 2: Identify nodes in the implication graph

- Fact, outcome and logical operators nodes from the sample rules

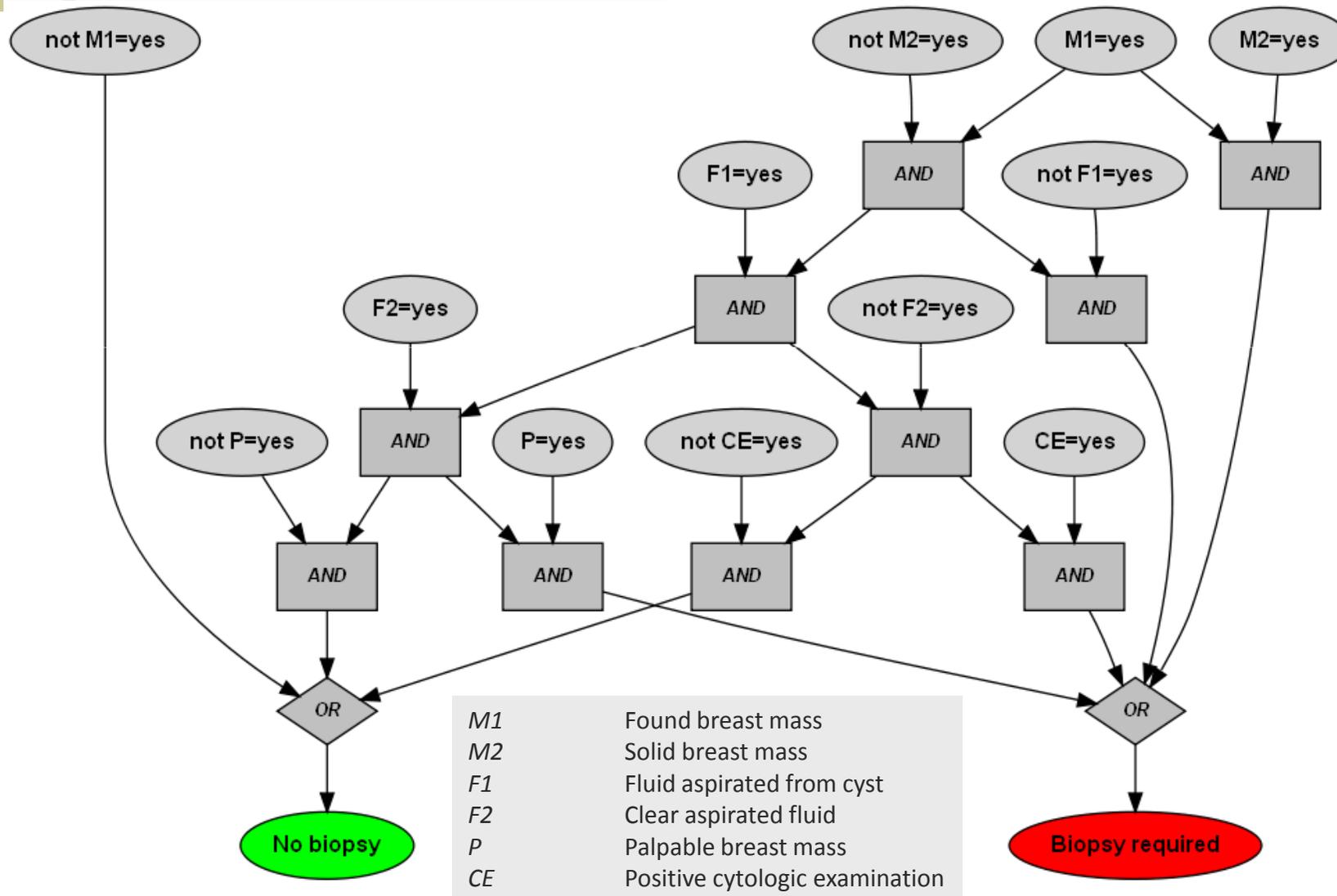


Step 3: Identify arcs in the implication graph

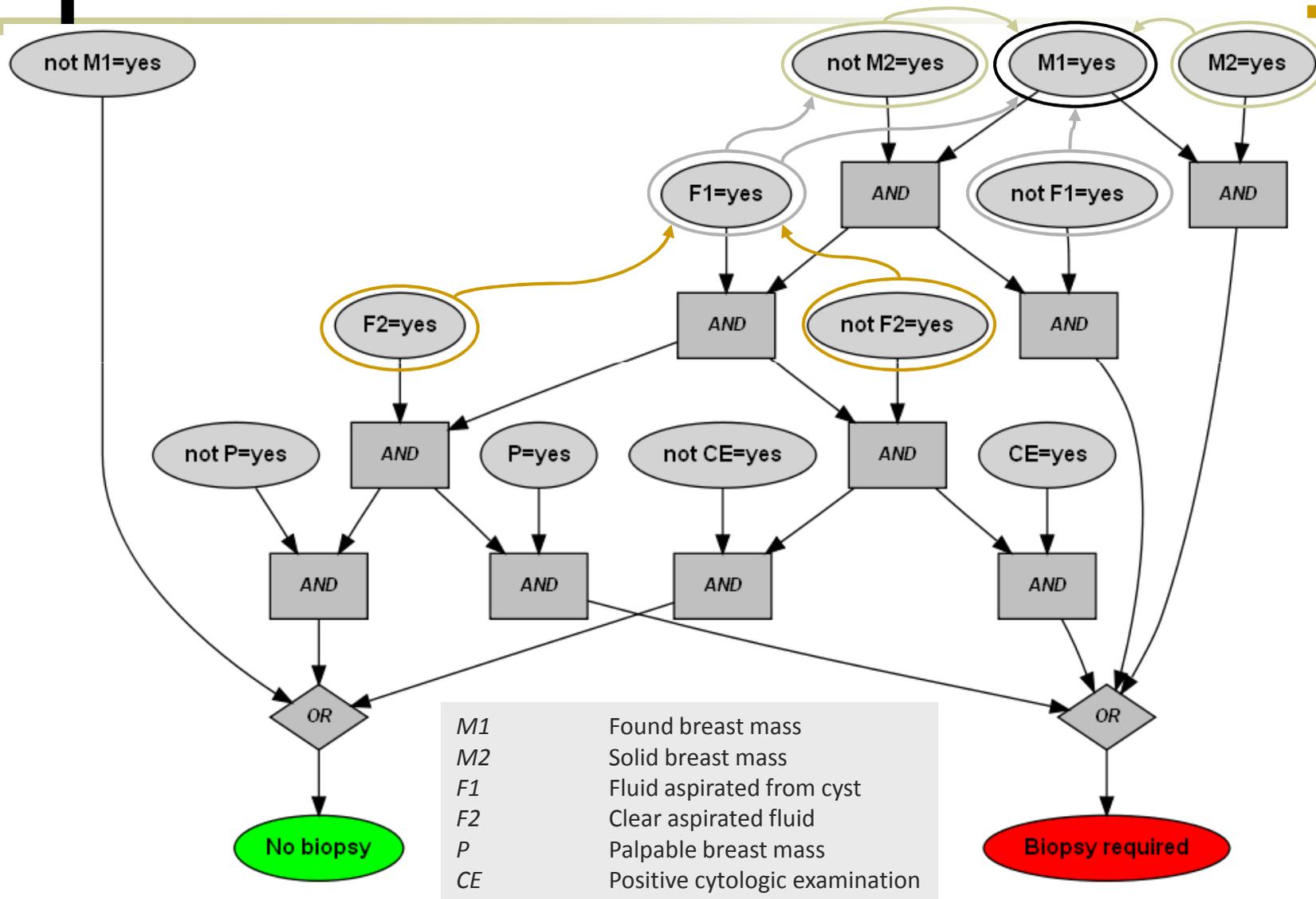
- Establishing arcs connecting the nodes from the sample rules



Implication Graph for BM CPG



Implication Graph for BM CPG



Reasoning from the CPG: Terminology

- *Outcome*: one of N possible diagnoses (or recommendations) resulting from following a CPG (i.e. biopsy required).
- *Solution*: A set of clinical findings and the corresponding outcome. It is represented as a path in the implication graph (i.e. M1=yes, M2=yes, biopsy required).

Reasoning from the CPG: Input/Output

- Input data:
 - *Initial Clinical Results (ICR)*: Known clinical findings (facts) about the patient (clear fluid was aspirated)
 - *Background Knowledge (BK)*: A set of (meta) facts representing relationships between clinical findings (can aspirate fluid only from cystic breast mass)
 - *Query (Q)*: ICR linked with an outcome.
- Output:
 - A set of solutions for a given Q.

Reasoning process

- Load BK
- Load implication graph
- Input ICR
- Add clinical results (CR) through deduction using ICR and BK
 - $CR \leq \text{deduce}(\text{ICR}, \text{BK})$
- Input Q
- Generate the solutions. This is achieved by using Prolog's goal-driven reasoning process

Internal Representation of Implication Graph

- **Meta-facts – test_result(Test, Value, Source)**

```
test_result(M1(yes), true, given).
test_result(not(M1(yes)), false, deduced).
test_result(not(M2(yes)), true, deduced).
test_result(CE(yes), unknown, unknown).
```

- **Examining values of meta-facts**

```
check_test(Test, Value) :-
    test_result(Test, Value, deduced).

check_test(Test, Value) :-
    test_result(Test, Value, given).

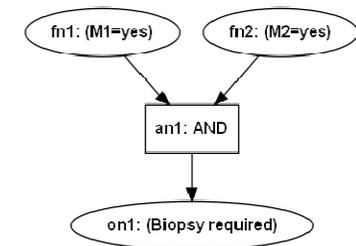
check_test(Test, Value) :-
    test_result(Test, unknown, _).
```

Internal Representation of Implication Graph

■ Solution

- (M1=yes) AND (M2=yes) → Biopsy required

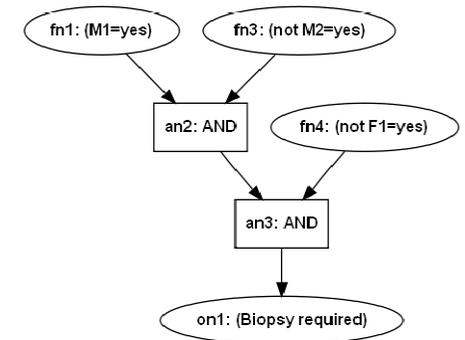
```
outcome(on1) :-                                     % on1/an1  
    check_test(M1(yes), true),                       % fn1  
    check_test(M2(yes), true).                       % fn2
```



- (M1=yes) AND (not M2=yes) AND (not F1=yes) → Biopsy required

```
outcome(on1) :-                                     % on1/an3  
    check_test(not(F1(yes)), true) % fn4  
    check_operator(an2). % an2
```

```
check_operator(an2) :-                               % an2  
    check_test(M1(yes), true),                       % fn1  
    check_test(not(M2(true)), true). % fn3
```



Background Knowledge

Knowing		Implies	
Test	Value	Test	Value
M2(yes)	true/false	M1(yes)	true
F1(yes)	true/false	M1(yes)	true
F2(yes)	true/false	F1(yes)	true
F1(yes)	true/false	M2(yes)	false

M1 Found breast mass
M2 Solid breast mass
F1 Fluid aspirated from cyst
F2 Clear aspirated fluid
P Palpable breast mass
CE Positive cytologic examination

Deduction

Facts

Before

```
test_result(M1(yes), unknown, unknown).
test_result(M2(yes), unknown, unknown).
test_result(F1(yes), true, given).
test_result(F2(yes), unknown, unknown).
test_result(P(yes), unknown, unknown).
test_result(CE(yes), unknown, unknown).
```

Deduction

```
(F1(yes), true) => (M1(yes), true)
(F1(yes), true) => (M2(yes), false)
```

After

```
test_result(M1(yes), true, deduced).
test_result(M2(yes), false, deduced).
test_result(F1(yes), true, given).
test_result(F2(yes), unknown, unknown).
test_result(P(yes), unknown, unknown).
test_result(CE(yes), unknown, unknown).
```

<i>M1</i>	Found breast mass
<i>M2</i>	Solid breast mass
<i>F1</i>	Fluid aspirated from cyst
<i>F2</i>	Clear aspirated fluid
<i>P</i>	Palpable breast mass
<i>CE</i>	Positive cytologic examination

Sample Query Result

```
?- cpg_solutions(biopsy_required).
```

```
Adding new fact to KB : knowing(F1(yes), true) => implies(M1(yes), true)
```

```
Adding new fact to KB : knowing(F1(yes), true) => implies(M2(yes), false)
```

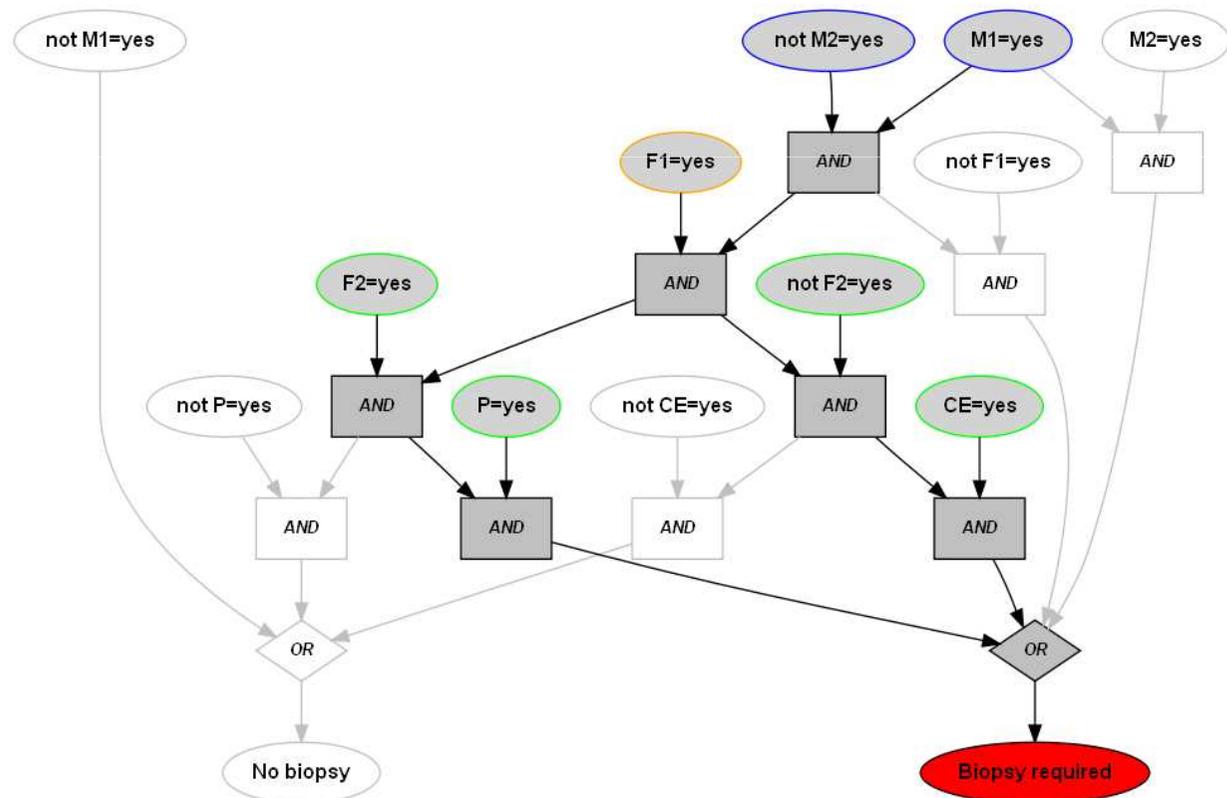
```
--- 1 ---
```

```
deduced(true(M1(yes)))
deduced(false(M2(yes)))
true(F1(yes))
assume(true(F2(yes)))
assume(true(P(yes)))
```

```
--- 2 ---
```

```
deduced(true(M1(yes)))
deduced(false(M2(yes)))
true(F1(yes))
assume(false(F2(yes)))
assume(true(CE(yes)))
```

M1	Found breast mass
M2	Solid breast mass
F1	Fluid aspirated from cyst
F2	Clear aspirated fluid
P	Palpable breast mass
CE	Positive cytologic examination



Discussion



- Use of CPG with incomplete data
- Identification of inconsistencies
- Explanation of the results
- Need to codify BK
- Need for expert advice with moving from textual CPG to decision graph
- Difficult to represent temporal processes

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