A Constraint Satisfaction Approach to Data-Driven Implementation of Clinical Practice Guidelines

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AMIA Annual Conference
November 12, 2008

Outline

1. Clinical practice guidelines (CPG)
   - Main research directions
   - Issues
2. Representation of CPG as a constraint satisfaction model
3. Methodology
   - Three steps
   - Example using CAEP pediatric asthma guideline
4. Future work

1. Clinical Practice Guidelines

- Emerged out of need to reduce patient management variability, control costs, improve patient outcomes
- Aimed to provide evidence for use at point of care
- Mostly represented as tables or flowcharts

Guideline Modeling Languages

- Represent processes/states through primitives – action step, patient state, decision step, case step
- A process model determines factors such as temporal order or nesting of guidelines
- Underlying data model that provides the detail or domain knowledge for the guideline

Table 1. Representation primitives for actions, decisions, patient states, and execution states in the reviewed guideline representation models.

Guideline Models	Actions	Decisions	Patient States	Execution States
Arden Syntax	action slot	logic slot	no	no
DILEMMA/PRESTIGE	protocol	state transition	n/a	procedure state
EON/DHARMA	action, activity	decision	scenario, activity state	no§
PROforma	action, enquiry	decision	n/a	task state
Siegfried	recommendation	logic	no	no
GLIF	action step	decision step	patient state step	no§
Asbru	plan	condition, preference	temporal patterns	plan state
GUIDE/PatMan	task, wait, monitor	decision	(implicit in Petri Net)	n/a
PRODIGY	action, activity	decision	scenario	n/a
GASTON	action	decision	n/a	n/a
Torino	work action, query action	decision action	conclusion	n/a

n/a: information not available from the publications

§ EON/DHARMA and GLIF has execution states, but they are not in the guideline representation model

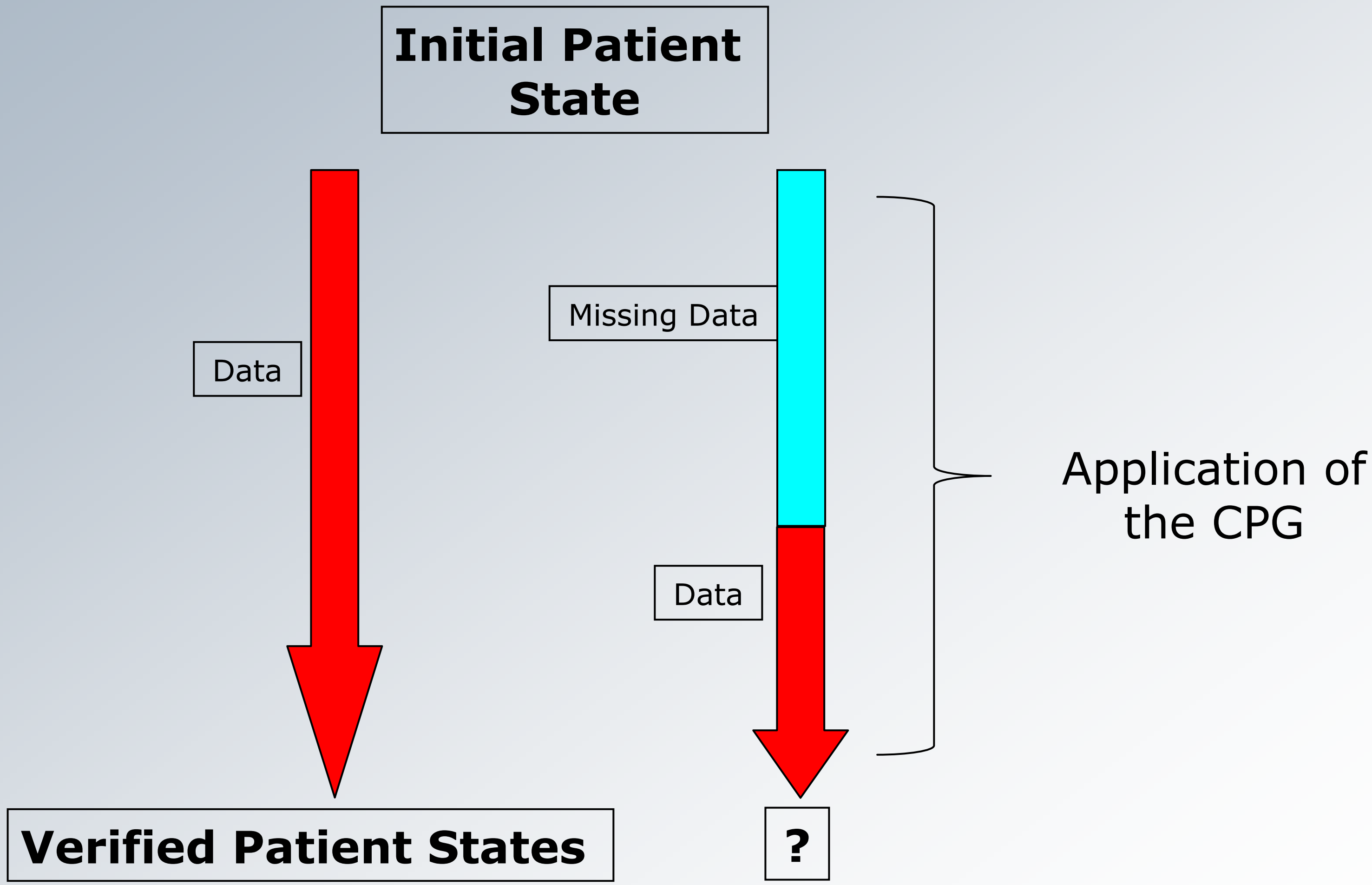
Issues

- Difficult to use in presence of missing data
- A gap between guidelines representation and clinical implementation (Waitman and Miller 2004)
- Need to cater to different levels of clinical decision making expertise?

Extending CPG Research

- Develop a data-driven model that works with incomplete patient data
- Develop a flexible model that permits site-specific customization
- Expand the patient state step for more comprehensive decision making

Clinical Use



2. A Constraint Satisfaction (CSP) Model

- Constraints define allowable relationships between (variable, value) pairs
- Vector of incomplete (variable, value) pairs (available patient state data) is an input to a model
- Solutions (possible patient management paths) built on the input vector are generated

3. Three Step CSP Approach

- Clinician collects patient data pertinent to patient state
  - Step 1 – Use patient state data to solve the CSP for a feasible solution(s); – if they exist, present them, otherwise identify reason for infeasibility, remove the violating (variable, value) pair(s) and create a revised patient state model
  - Step 2 – use the revised patient state data to solve the CSP to determine all feasible solutions
  - Step 3 – Order the feasible solutions
- The feasible solution is presented to the clinician with a description of what (variable, value) pairs are needed to instantiate the solution

Clinical Example - CAEP Pediatric Asthma CPG

- Created for ED management to determine severity of pediatric asthma exacerbation (mild, moderate, severe) using 8 clinical signs and 3 clinical measurements.
- Issue: how to use asthma CPG in light of incomplete patient data?
- Example: only 5 assessments are done and a diagnostic decision of mild exacerbation is made (patient state):
- **Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Typical_episode(worse), Exacerbation(mild)**

CSP Model Development

- Variables and their domains

  Dyspnea [exertional, at_rest, labored], Beta_agonist [good_response, partial_response, weak_response, no_response], Difficult_speech [absent, moderate, present], Tachycardia [absent, present], etc.

- Constraints
  - Unary partial-patient-descriptor: Dyspnea(exertional) AND Exacerbation(mild)
  - Complete-patient-descriptor: Dyspnea(at_rest) AND Beta_agonist(partial_response) AND Difficult_speech(absent) AND Tachycardia(absent) AND Tachypnea(at_rest) AND Accessory_muscules(none) AND Breathing_sounds(reduced) AND Typical_episode(same) AND SaO2(92_95) AND PEV(50_75) AND FEV(50_75) AND **Exacerbation(moderate)**
- Feasible solution
  - Any set of (variable, value) pairs that satisfies complete-patient-descriptor constraints and meets the unary constraints

Three Step Approach – Step 1: Consistency Check

- Input vector: Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Typical_episode(worse), Exacerbation(mild)
- Check if all input (variable, value) pairs satisfy unary constraints

Typical_episode(worse) does not satisfy:

Typical_episode(better) AND Exacerbation(mild)
Typical_episode(same) AND Exacerbation(mild)

- Variable Typical_episode is removed from the patient state to create revised input vector: Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Exacerbation(mild)

Step 2: Solve a Model

- For revised input vector use backtracking to solve the CSP for all feasible solutions
    - Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(normal), **Typical_episode(better)**, SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)
    - Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(reduced), **Typical_episode(better)**, SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)
    - Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(normal), **Typical_episode(same)**, SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)
    - Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(reduced), **Typical_episode(same)**, SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)

Step 3: Order Feasible Solutions

- Feasible solutions are ordered according to ascending conflict value for conflicting (variable, value) pairs in the original input vector (Step 1)
  - Typical_episode(worse) conflicts with Typical_episode(same) and Typical_episode(better); Assuming that better>same>worse, ordered presentation is:

    1. Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(normal), Typical_episode(same), SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)

    2. Dyspnea(exertional), Beta_agonist(good_response), Difficult_speech(absent), Tachycardia(absent), Tachypnea(exertional), Accessory_muscules(none), Breathing_sounds(reduced), Typical_episode(same), SaO2(>95), PEV(>75), FEV(>75), Exacerbation(mild)

  - Ordering suggests that patient with mild exacerbation has current episode the same as typical episode from the past. Discrepancy with the original input value should prompt MD to re-evaluate clinical assessments or diagnosis

4. Future work

- Develop the heuristic to rank the feasible solutions
- Create the generic CSP model to represent patient state step in the CPG
- Apply reasoning to the model to infer likely management paths (use predicate logic and Logic-based Truth Maintenance System to facilitate induction)
- Conduct usability study with clinicians at Children's Hospital of Eastern Ontario (CHEO)

Thank you

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