Data Mining Based Decomposition for Assume Guarantee Reasoning

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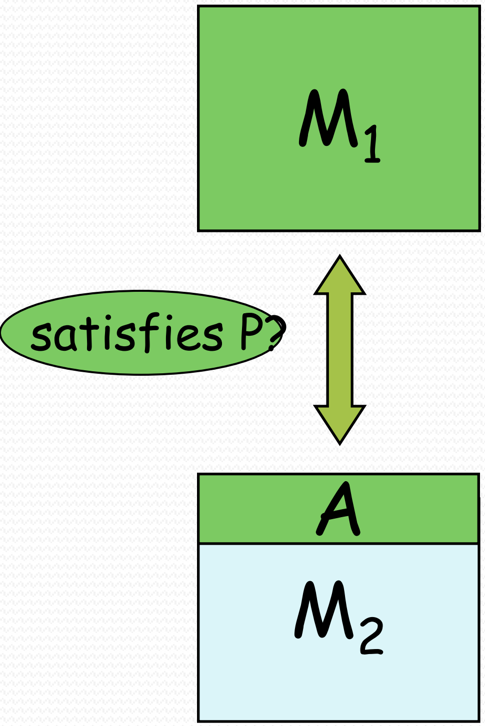
Outline

- Introduction
- Data Mining based Decomposition
- Experimental Results
- Conclusion

Compositional Verification



- Model Checking …… state space explosion
- Divide and conquer
- Decompose properties of system (M_1 || M_2) in properties of its components
- Does M_1 satisfy P?
  - typically a component is designed to satisfy its requirements in *specific* contexts / environments
- Assume-guarantee reasoning: introduces assumption A representing M_1's "context"
- Simplest assume-guarantee rule

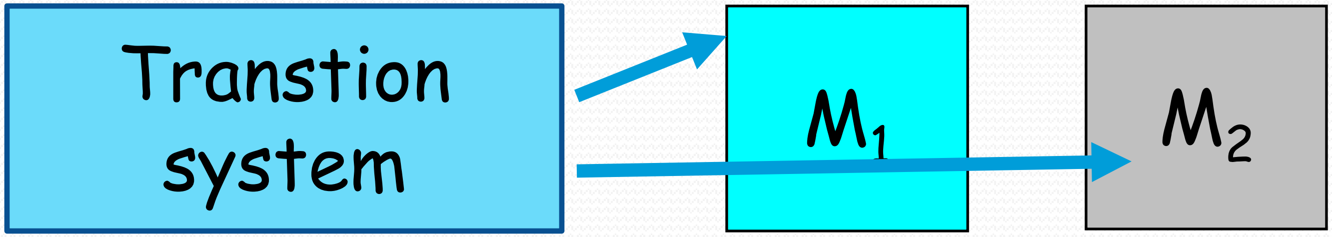
$$\frac{\begin{array}{llll} 1. & \langle A \rangle & M_1 & \langle P \rangle \\ 2. & \langle \mathit{true} \rangle & M_2 & \langle A \rangle \end{array}}{\langle \mathit{true} \rangle\ M_1 \mid\mid M_2\ \langle P \rangle}$$

Automatic Assume-Guarantee Reasoning

- 2 key steps in assume-guarantee based verification
  - Identifying an appropriate decomposition of the system,
  - Identifying simple assumptions.
- Our Goal
  - automatically decompose a system into several modules?
  - The resulting model should be convenient for assume-guarantee reasoning
    - Minimizing interactions between modules
    - It can benefit the assumption learning.

Related Works

- Learning Assumptions for Compositional Verification, (Cobleigh et al., *2003*).
  - Given a set of decomposed modules
  - Use L* algorithm to learn assumption automatically.
- Learning-based Symbolic Assume-guarantee Reasoning with Automatic Decomposition , (Nam and Alur, *2005-2006*)
  - The first paper on system decomposition for AG
  - Use hypergraph partitioning to decompose the system



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Motivating Example

- Consider a simple example.

```
VAR g, a, b, p, c;
Next(g) := a & b;
Next(p) := g | c
Next(c) := !p
```

g is dependent on *a* and *b*.

X:

a, b, g, p, c

T:

t_g: g a b

t_p: p g c

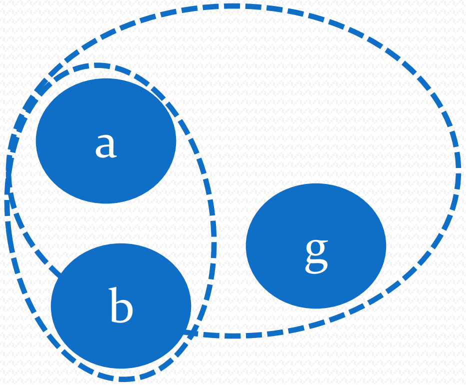
t_c: c p

Decomposition Strategy

- Target:
  - Reduce the shared variables as much as possible,
  - such that assumptions are based on a small language alphabet.
- Appropriate Decomposition:
  - Enhance inner-cohesion (within a partition)
  - Minimize inter-connection (between partitions)
- Heuristic:
  - Try to put the dependent variables together.

How to minimize inter-connection?

- Construct Weighted Hypergraph:
  - Using data mining
- Weighted Hypergraph:
  - The edge connect arbitrary vertices.
  - The edge is assigned a numerical value.
- Weighted Hypergraph partitioning:
  - Partitioning the hypergraph into *K* parts.
  - The sum of weight of all edges connecting different parts is minimal.



How to enhance inner-cohesion?

- Using a data mining algorithm: Association rule mining.
- Association rule mining discovers item implications through a large data set.

item

transaction

	a	b	c	g	p
t_g	1	1	0	1	0
t_p	0	0	1	1	1
t_c	0	0	1	0	1

- An association rule $X \Rightarrow Y$, means if X occurs in a transaction, then Y should occur too.

Association Rule Mining

- Two steps for using association rule mining
  - Find frequent itemsets with minimum support;
  - Generate association rules from these itemsets with minimum confidence.

- Some important concepts
  - The *support* of an itemset X: the number of records that satisfy X divided by the number of records.
  - The *confidence* of a rule $X \Rightarrow Y$: the number of records that satisfy $X \cup Y$ divided by the number of records that satisfy X.

- Find frequent itemsets E_{fi} .
- Generate rules from frequent itemset.

V_T:

t_g: g a b

t_p: p g c

t_c: c p

Frequent item sets

a b

a b g

a g

b g

p c

p g

p g c

c g

Association rules

$a \Rightarrow b$	100
$b \Rightarrow a$	100
$b\ g \Rightarrow a$	100
$g \Rightarrow a$	50
$g \Rightarrow b$	50
$c \Rightarrow g$	50
$p \Rightarrow c$	100
$p \Rightarrow g$	50
… …	

Construct Weighted Hypergraph

- Create a hyperedge from each frequent itemset
  - Variables are the vertices
  - hyperedge connects the variables
  - Each itemset gives a possible combination for the items.
- Weight of a hyperedge is decided by the average value of all rules derived from the corresponding itemset.
  - For example, the weight of edge (p, g, c) is decided by three rules: $p\ g \Rightarrow c$, $p\ c \Rightarrow g$, and $g\ c \Rightarrow p$.

This value gives an evaluation for the interactions between items.

```
VAR g, a, b, p, c;
Next(g) := a & b;
Next(p) := g | c
Next(c) := !p
```

variable transactions

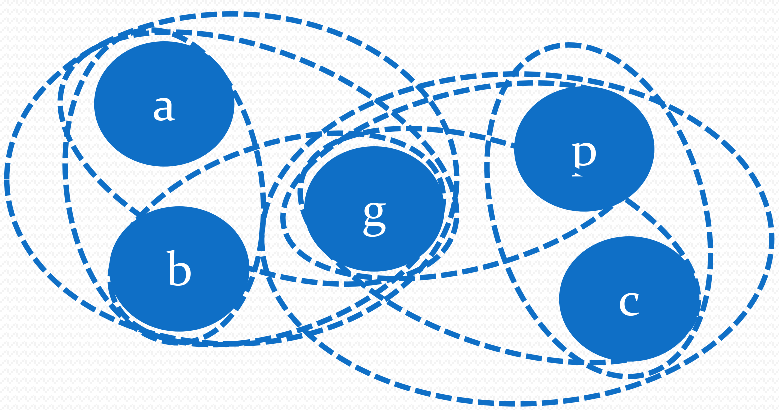
g	a	b
p	g	c
c	p	

frequent item set

Hyperedges:

a b	100
a b g	100
a g	75
b g	75
p c	100
p c g	50
p g	50
c g	50

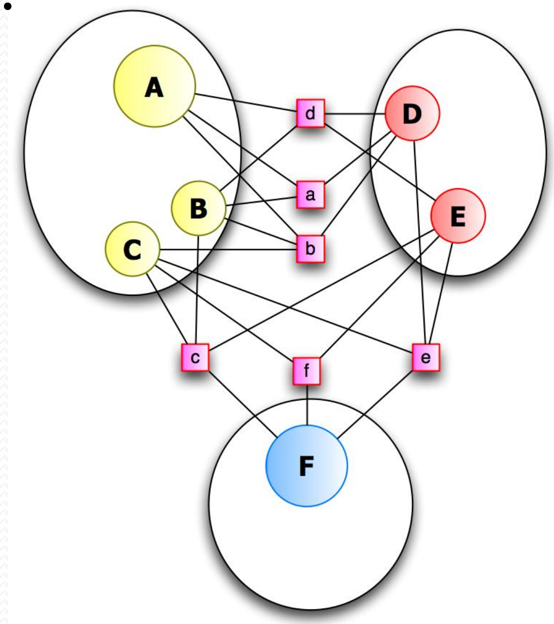
modeling



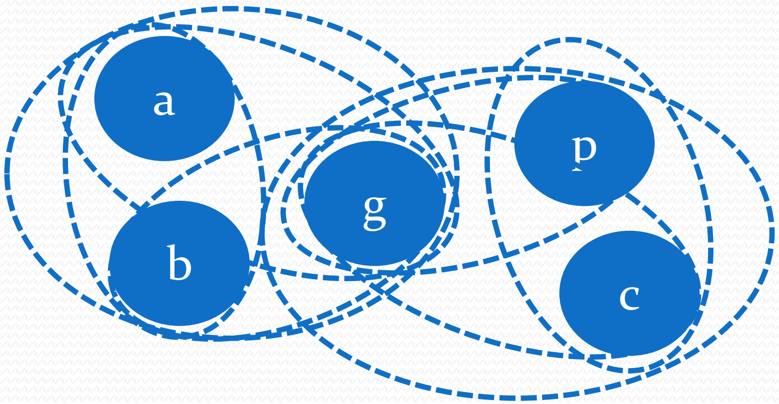
Weighted Hypergraph Model

Decomposition as Hypergraph Partitioning

- Hypergraph partitioning:
  - Partitioning the hypergraph into K parts.
  - Minimize sum weights of all cut-edges

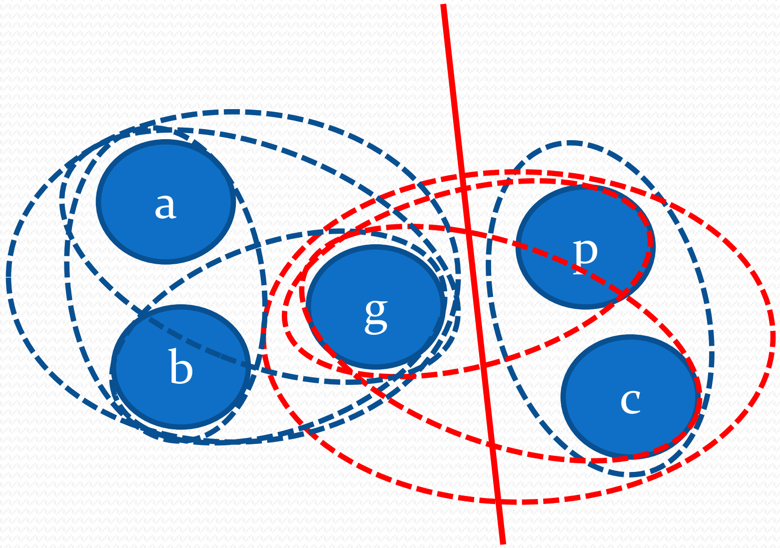


- There are some existing tools for hypergraph partitioning problem, among them, we chose hMETIS.



Hyperedges:

a b	100
a b g	100
a g	75
b g	75
p c	100
p c g	83.3
p g	50
c g	50



Hyperedges:	
a b	100
a b g	100
a g	75
b g	75
p c	100
p c g	83.3
p g	50
c g	50

- Decomposing the variable set into 2 partitions:
  - *a*, *b*, *g* and *p*, *c*.

System Decomposition

- With the variable partition result

```
VAR g, a, b, p, c;
Next(g) := a & b;
Next(p) := g | c
Next(c) := !p
```

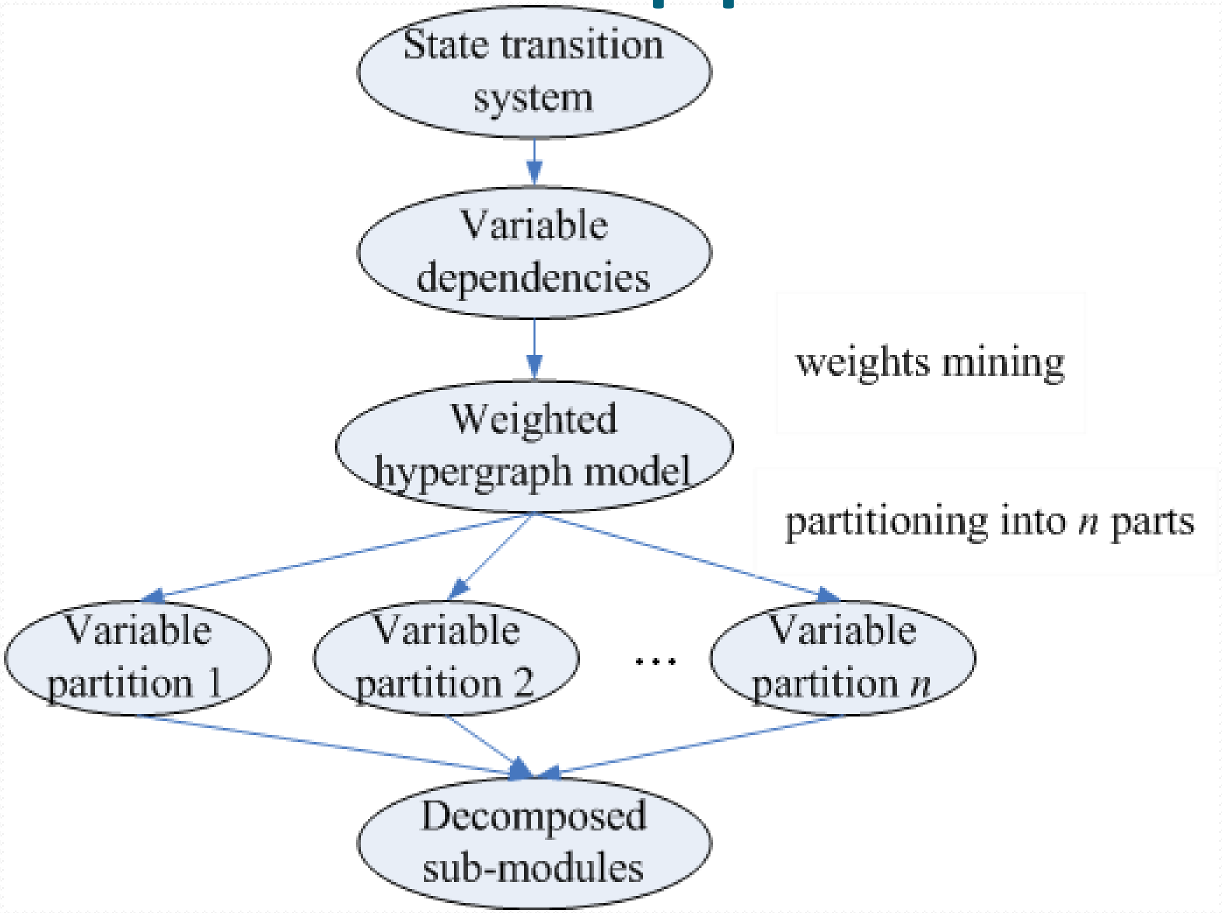
p,c

g,a,b

```
VAR p, c;
Next(p) := g | c
Next(c) := !p
```

```
VAR g, a, b;
Next (g) :=  a & b;
```

The Flow of our Approach



Benefits of Our Approach

- Modules are compact and have fewer communication.
- Each module has less requirements on its environment ➔ simplify assumption

$$\frac{\begin{array}{llll} 1. & \langle A \rangle & M_1 & \langle P \rangle \\ 2. & \langle true \rangle & M_2 & \langle A \rangle \end{array}}{\langle true \rangle\ M_1 \,||\, M_2\ \langle P \rangle}$$

- Since *A* is reduced, the efforts for verifying these two premises are also reduced.

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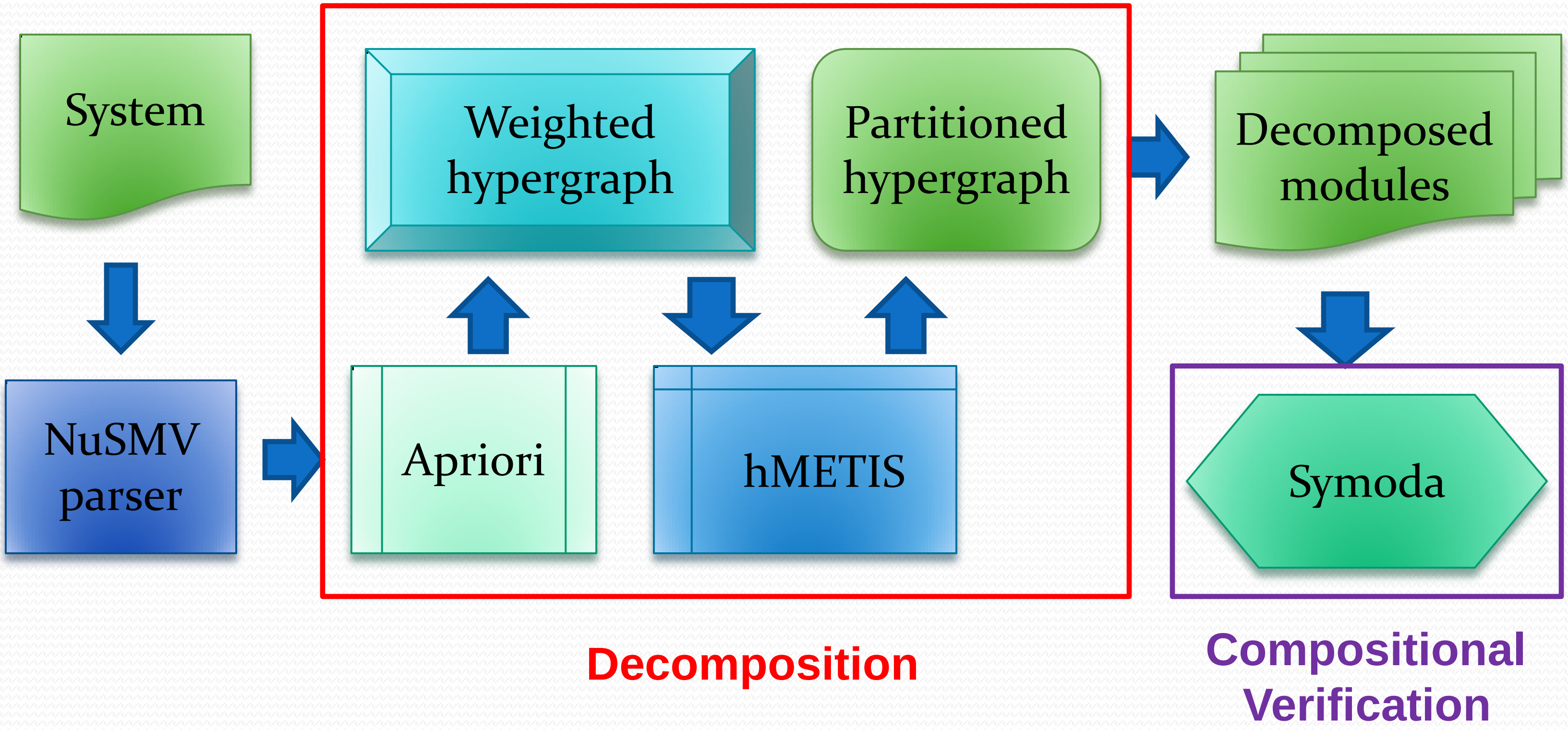
Implementation



Experimental Results

Benchs	Var	Weighted Hypergraph		Unweighted Hypergraph		General
		IO	time	IO	time	
s1a	23	2	0.32	2	0.31	15.77
s1b	25	6	0.49	6	0.60	16.03
msi3	61	17	2.81	19	3.53	10.23
msi5	97	24	5.86	32	8.81	27.17
msi6	121	27	9.69	33	12.11	43.80
syncarb10	74	32	76.13	33	129.20	Timeout
peterson	9	7	0.65	7	113.8	27.67
guidance	76	37	19.93	13	4.11	18.75

- Most of our experiments leads to good result.
- Negative result in *guidance*,
  - The variables dependencies in *guidance* are so sparse

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Conclusion and Future work

- New decomposition method for assume-guarantee
  - Integrates data mining to the compositional verification.
  - Using weighted hypergraph partitioning to cluster variables.
- Automatic decomposition approach
  - Inner cohesion improved
  - Inter connection reduced
- Experimental results show promise
- Future work include:
  - Circular assume-guarantee rules.
  - Applying assorted classification methods in data mining to find even better decomposition.

Thank You !

Question & Answer