

Weighted Automata and Concurrency

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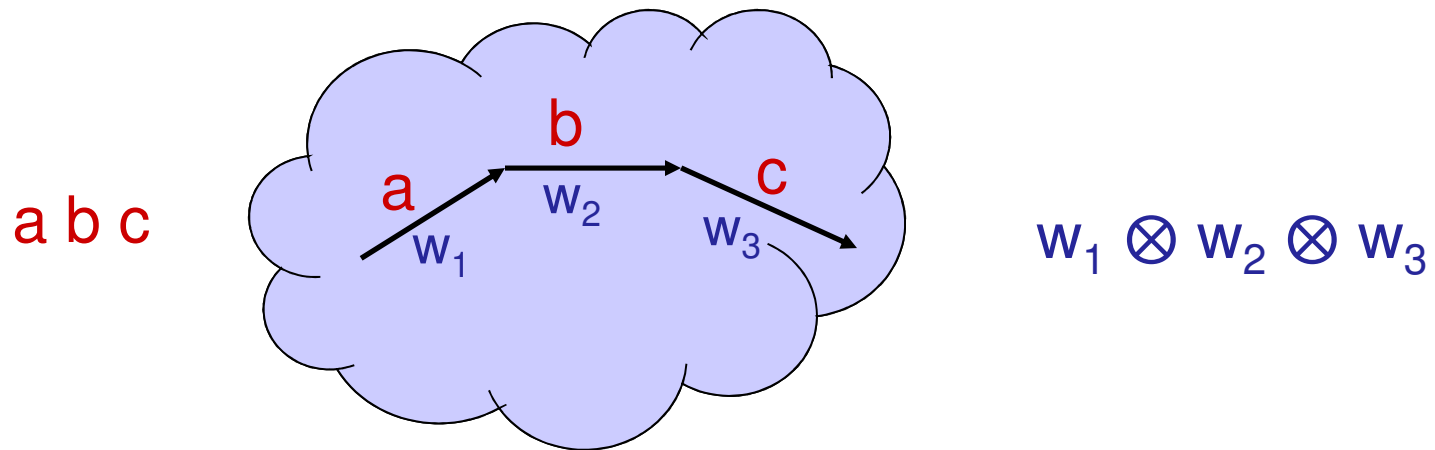
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Weighted Automata

- A finite-state machine with weights



- A normal FSM: word \rightarrow Bool
- Weighted Automata: word \rightarrow Weight

Outline

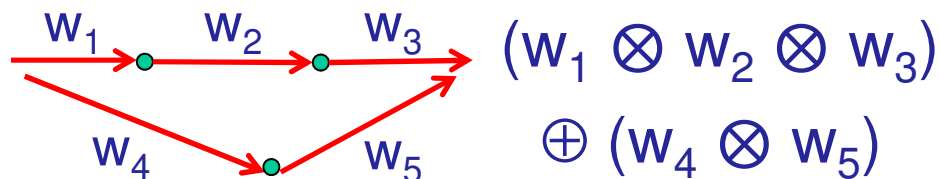
- Define weights and weighted automata
- Intersecting weighted automata
- Application
 - Generalizes to composition of weighted transducers
 - Context-Bounded Analysis: Interprocedural dataflow analysis of concurrent programs, under a bound on the number of context switches

↑
Earlier talks

What are Weights?

- Weights == Dataflow transformers
 - Technically, they are elements of a semiring

Semiring	Dataflow Analysis
D : set of weights	DataFacts \rightarrow DataFacts
\otimes : extend $D \times D \rightarrow D$	<i>Compose</i> (extends paths) $\tau_1 \otimes \tau_2 = \tau_2 \circ \tau_1$
\oplus : combine $D \times D \rightarrow D$	<i>Meet</i> (combines paths) $\tau_1 \oplus \tau_2 = \lambda d. \tau_1(d) \sqcap \tau_2(d)$



Weighted Automata

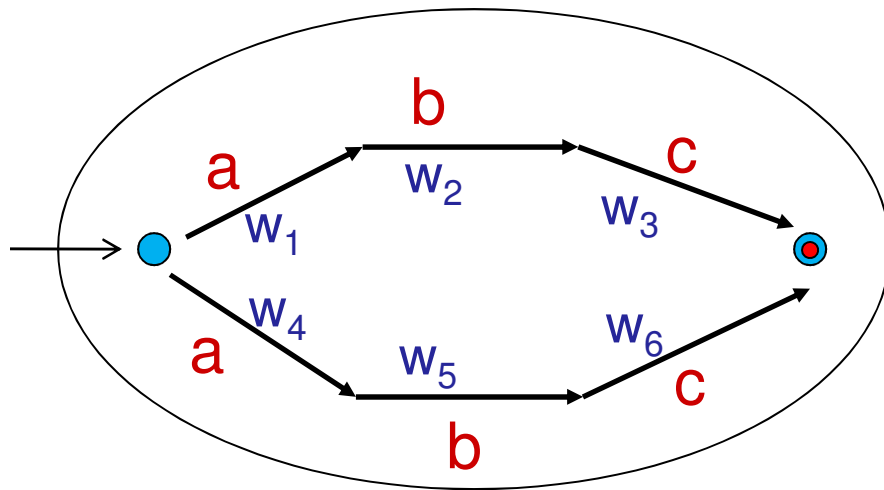
Definition 2. A bounded idempotent semiring (or “weight domain”) is a tuple $(D, \oplus, \otimes, \bar{0}, \bar{1})$, where D is a set of weights, $\bar{0}, \bar{1} \in D$, and \oplus (combine) and \otimes (extend) are binary operators on D such that

1. (D, \oplus) is a commutative monoid with $\bar{0}$ as its neutral element, and where \oplus is idempotent. (D, \otimes) is a monoid with the neutral element $\bar{1}$.
2. \otimes distributes over \oplus , i.e., for all $a, b, c \in D$ we have
$$a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c) \text{ and } (a \oplus b) \otimes c = (a \otimes c) \oplus (b \otimes c) .$$
3. $\bar{0}$ is an annihilator with respect to \otimes , i.e., for all $a \in D$, $a \otimes \bar{0} = \bar{0} = \bar{0} \otimes a$.
4. In the partial order \sqsubseteq defined by $\forall a, b \in D$, $a \sqsubseteq b$ iff $a \oplus b = a$, there are no infinite descending chains.

Note: extend need not be commutative

Weighted Automata

- $A: \text{word} \rightarrow D$
- $A(s) =$ combine of weights of all accepting paths for s
- $A(s) = \bigoplus \{ v(\sigma) \mid \sigma \text{ is an accepting path for } s \}$



$$A(\text{abc}) = (w_1 \otimes w_2 \otimes w_3) \oplus (w_4 \otimes w_5 \otimes w_6)$$

Weighted Automata

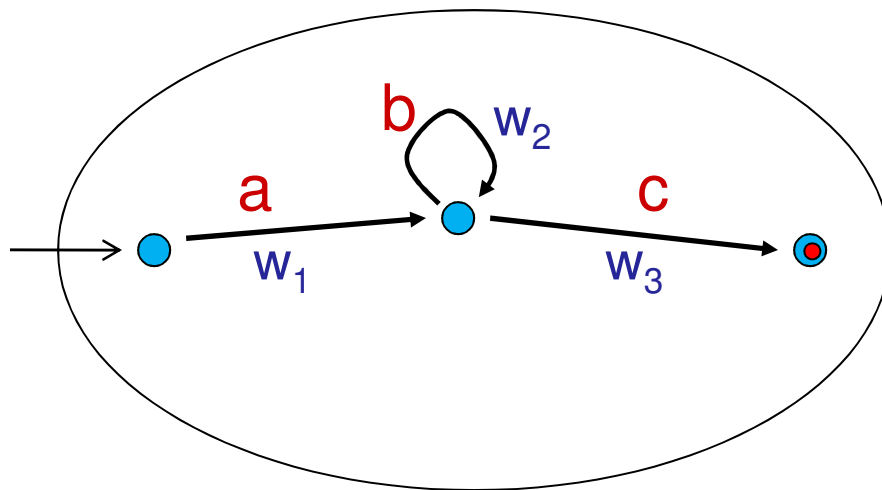
- $A(s) = \bigoplus \{ v(\sigma) \mid \sigma \text{ is an accepting path for } s \}$

A	A(s)
(Bool, \otimes is conj, \oplus is disj) “true” on all edges	True iff s is accepted
(Nat, \otimes is plus, \oplus is min) “1” on all edges	Length of shortest accepting path
(Distributive) Dataflow Analysis	Meet-Over-All-(accepting)-Paths

- $A(T) = \bigoplus \{ v(\sigma) \mid \sigma \text{ is an accepting path for } s \in T \}$
 $\bigoplus \{ A(s) \mid s \in T \}$

Weighted Automata

- Computing $A(T)$



$$\begin{aligned} A(ab^*c) &= \bigoplus_i \{ w_1 \otimes w_2^i \otimes w_3 \} \\ &= w_1 \otimes (\bigoplus_i w_2^i) \otimes w_3 \end{aligned}$$

$$A(ab^*c) = (w_1 \cdot w_2^* \cdot w_3)$$

$$x \cdot y = x \otimes y$$

$$x^* = (\bigoplus_i x^i)$$

$$(x \mid y) = x \oplus y$$

Weight domain properties:

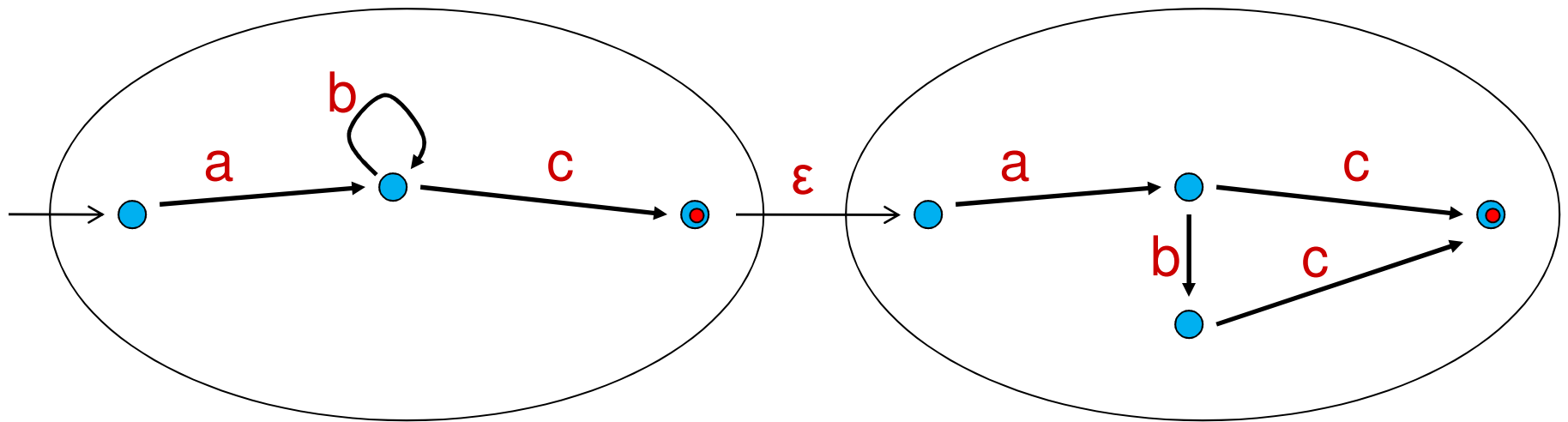
- Distributivity: $x \otimes (y \oplus z) = (x \otimes y) \oplus (x \otimes z)$
- Boundedness: All iterations x^* converge

Weighted Automata Intersection

- Given A_1 and A_2 , construct A_3 such that for all s ,
$$A_3(s) = A_1(s) \otimes A_2(s)$$
- If weight domain is (Bool, \otimes is conj, \oplus is disj) then
 - $A_3 = (A_1 \cap A_2)$

Weighted Automata Intersection

- $A_3(s) = A_1(s) \otimes A_2(s)$

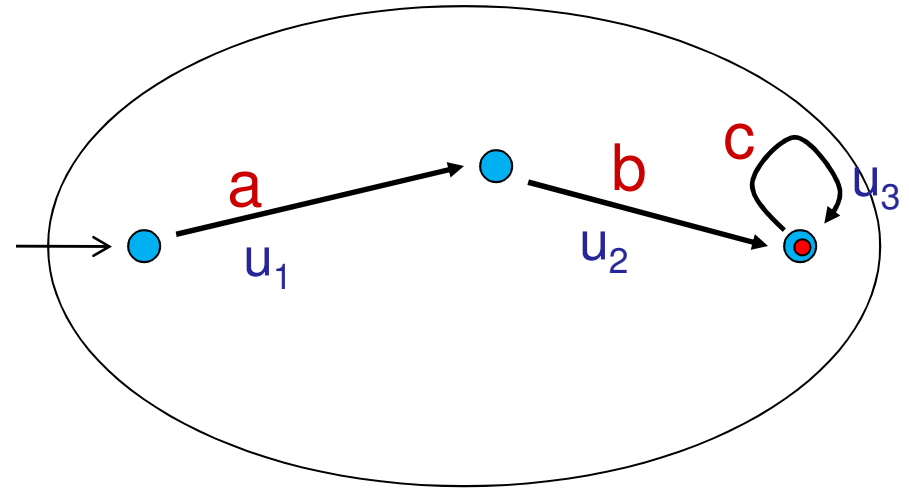
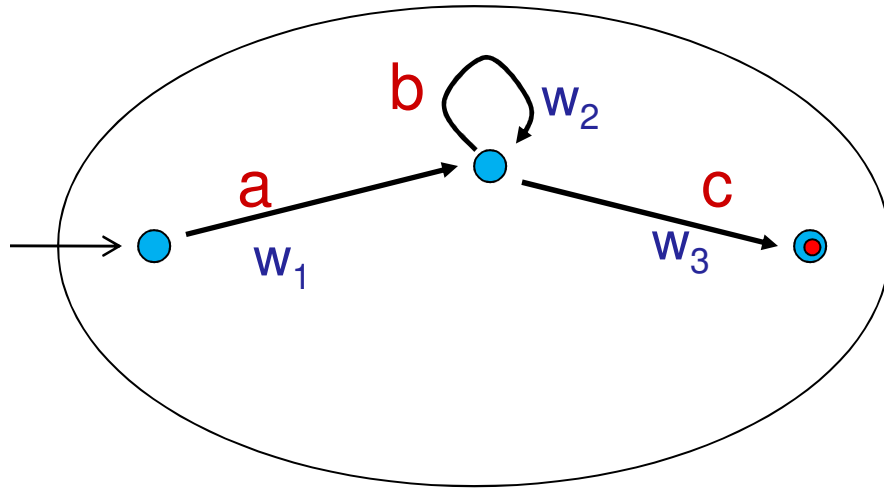


$$\begin{aligned}
 A_3(T) &= \bigoplus \{ A_3(s) \mid s \in T \} \\
 &= \bigoplus \{ A_1(s) \otimes A_2(s) \mid s \in T \} \\
 &\neq A_1(T) \otimes A_2(T)
 \end{aligned}$$

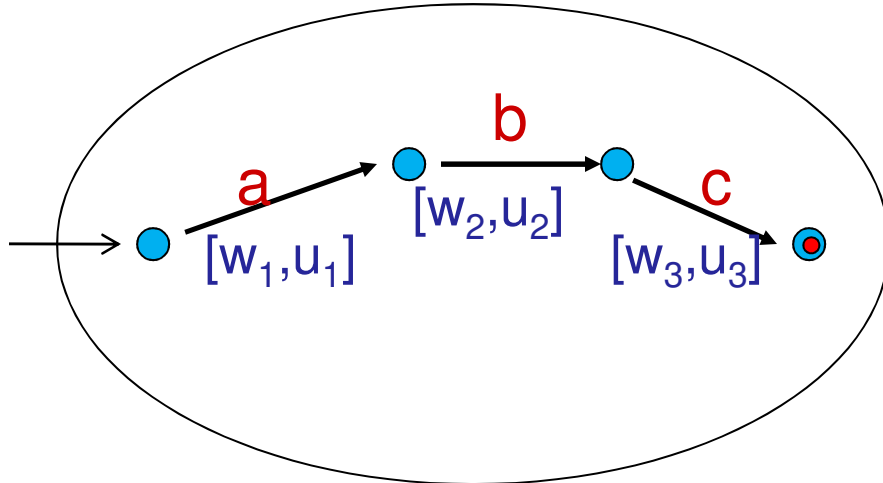
Given a regular set T , $\{ (s s) \mid s \in T \}$ is not regular

Weighted Automata Intersection

- $\forall s, A_3(s) = A_1(s) \otimes A_2(s)$

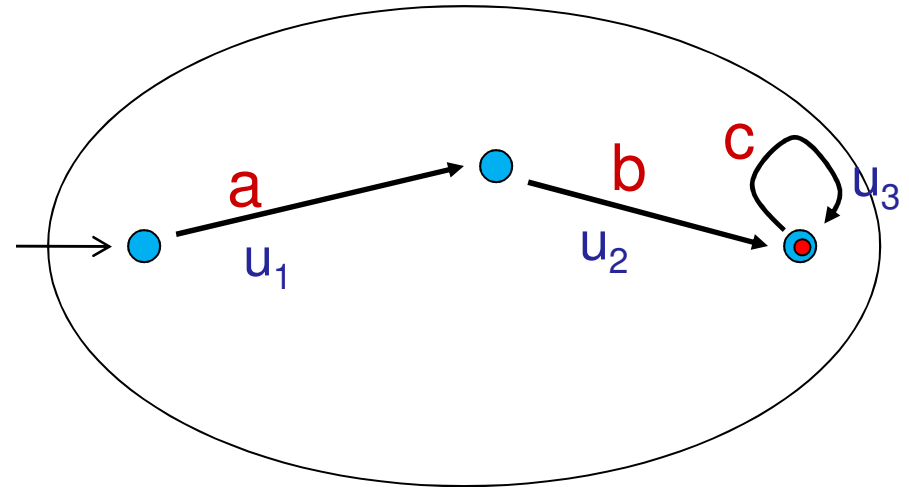
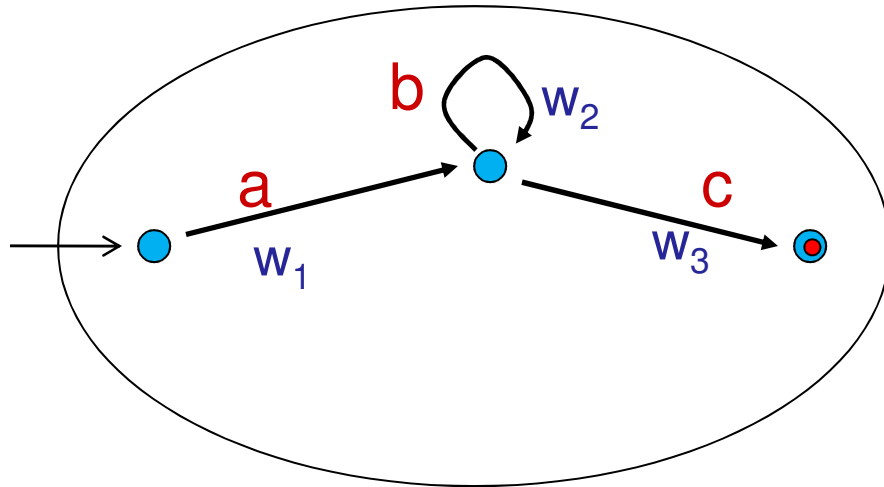


$$A_3(abc) = (w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3)$$

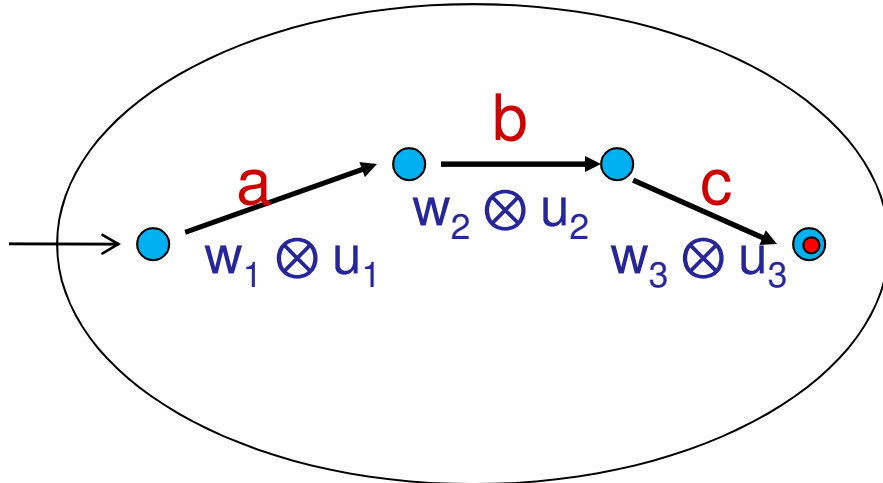


Weighted Automata Intersection

- $\forall s, A_3(s) = A_1(s) \otimes A_2(s)$



$$A_3(abc) = (w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3)$$



$$(w_1 \otimes u_1 \otimes w_2 \otimes u_2 \otimes w_3 \otimes u_3)$$

Tensor Product

- Given semiring (D, \otimes, \oplus) , construct a new semiring (D_T, \otimes, \oplus) to represent pairs of weights from D

$$\text{Tensor: } D \times D \rightarrow D_T$$

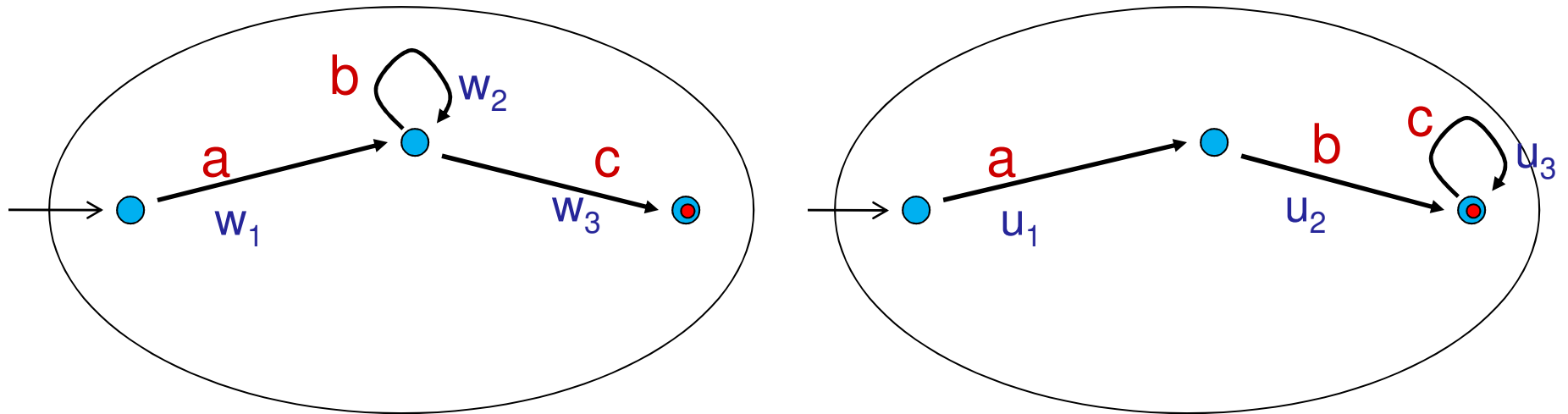
$$\text{DeTensor: } D_T \rightarrow D$$

- $\text{Tensor}(w_1, w_2) \otimes \text{Tensor}(w_3, w_4) = \text{Tensor}(w_1 \otimes w_3, w_2 \otimes w_4)$
- $\text{DeTensor}(\text{Tensor}(w_1, w_2)) = w_1 \otimes w_2$
- $\text{DeTensor}(W_1 \oplus W_2) = \text{DeTensor}(W_1) \oplus \text{DeTensor}(W_2)$

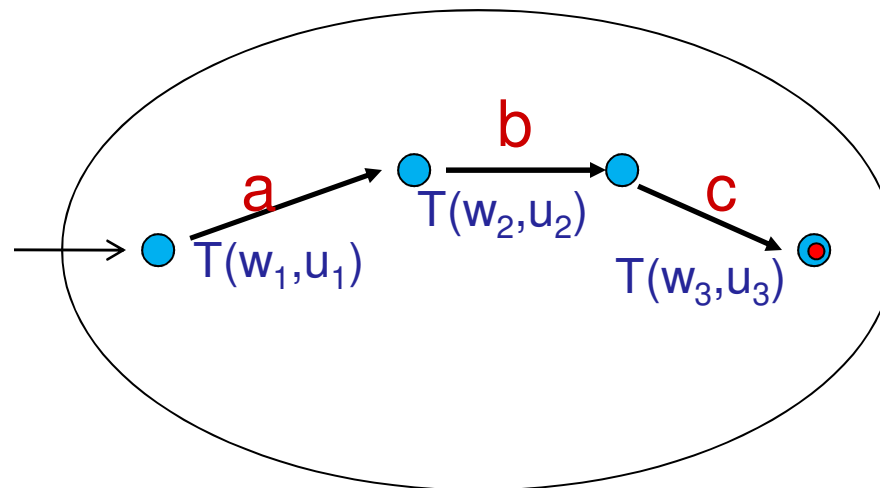
Note that D_T can be much bigger than $D \times D$

Weighted Automata Intersection

- $\forall s, A_3(s) = A_1(s) \otimes A_2(s)$

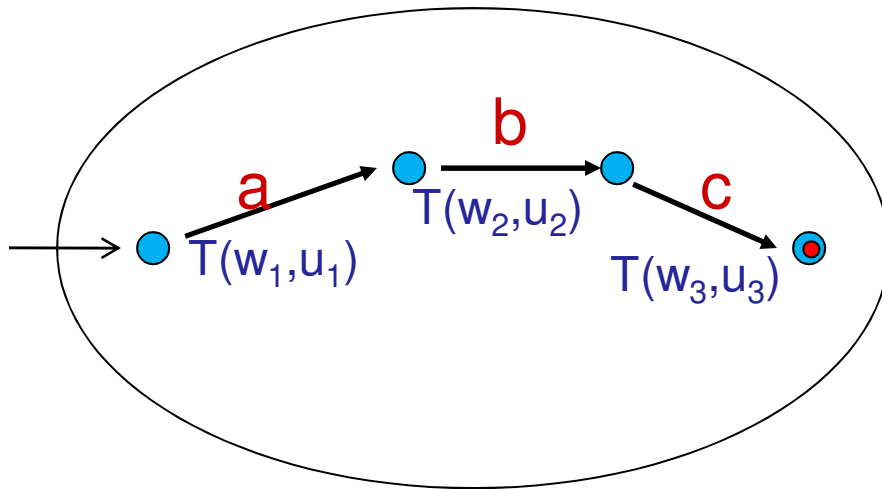


$$A_3(abc) = (w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3)$$

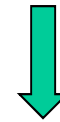


Weighted Automata Intersection

$$A_3(abc) = (w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3)$$



$$T(w_1, u_1) \otimes T(w_2, u_2) \otimes T(w_3, u_3) \\ = T(w_1 \otimes w_2 \otimes w_3, u_1 \otimes u_2 \otimes u_3)$$



DeTensor

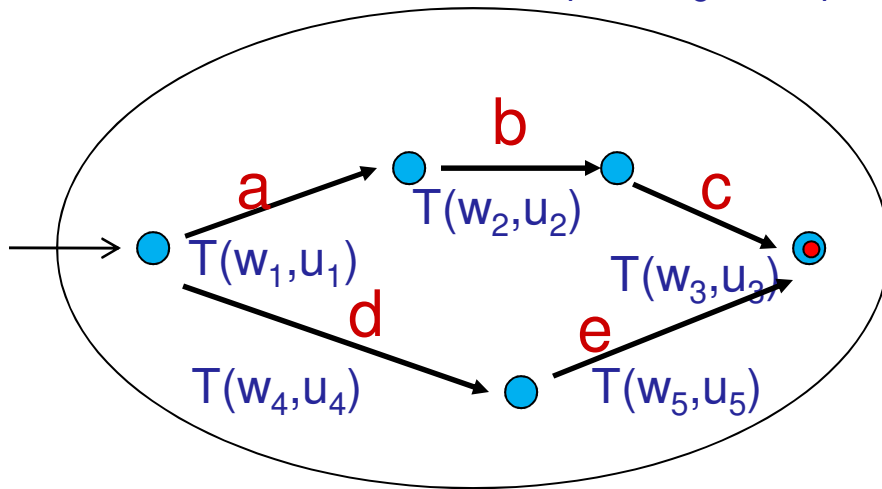
$$(w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3)$$

$$\text{Tensor}(w_1, w_2) \otimes \text{Tensor}(w_3, w_4) = \text{Tensor}(w_1 \otimes w_3, w_2 \otimes w_4)$$

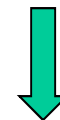
$$\text{DeTensor}(\text{Tensor}(w_1, w_2)) = w_1 \otimes w_2$$

Weighted Automata Intersection

$$A_3(\{abc, de\}) = (w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3) \oplus (w_4 \otimes w_5 \otimes u_4 \otimes u_5)$$



$$\begin{aligned} & T(w_1, u_1) \otimes T(w_2, u_2) \otimes T(w_3, u_3) \\ \oplus & T(w_4, u_4) \otimes T(w_5, u_5) \\ = & T(w_1 \otimes w_2 \otimes w_3, u_1 \otimes u_2 \otimes u_3) \\ \oplus & T(w_4 \otimes w_5, u_4 \otimes u_5) \end{aligned}$$



DeTensor

$$(w_1 \otimes w_2 \otimes w_3 \otimes u_1 \otimes u_2 \otimes u_3) \oplus (w_4 \otimes w_5 \otimes u_4 \otimes u_5)$$

$$\text{Tensor}(w_1, w_2) \otimes \text{Tensor}(w_3, w_4) = \text{Tensor}(w_1 \otimes w_3, w_2 \otimes w_4)$$

$$\text{DeTensor}(\text{Tensor}(w_1, w_2)) = w_1 \otimes w_2$$

$$\text{DeTensor}(W_1 \oplus W_2) = \text{DeTensor}(W_1) \oplus \text{DeTensor}(W_2)$$

Weighted Automata Intersection

Theorem: For any set of words T ,

$$\text{DeTensor}(A_3(T)) = \bigoplus \{A_1(s) \otimes A_2(s) \mid s \in T\}$$

$$\begin{aligned} \text{DeTensor}(\bigoplus \{A_3(s) \mid s \in T\}) &= \\ \bigoplus \{ \text{DeTensor}(A_3(s)) \mid s \in T \} &= \\ \bigoplus \{ \text{DeTensor}(\text{Tensor}(A_1(s), A_2(s))) \mid s \in T \} &= \\ \bigoplus \{A_1(s) \otimes A_2(s) \mid s \in T\} & \end{aligned}$$

Tensors

- Tensors are good, but do they exist?
 - Yes!
- If (D, \otimes) is commutative:
 - Then $D_T = D$, $\text{Tensor}(w_1, w_2) = w_1 \otimes w_2$, DeTensor is identity
- If D is the set of matrices over a commutative domain
 - Extend is matrix multiplication, combine is point-wise
 - Tensor is Kronecker product

Tensors

- Kronecker product

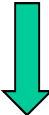
a_1	a_2
a_3	a_4

 \odot

b_1	b_2
b_3	b_4

 $=$

a_1b_1	a_1b_2	a_2b_1	a_2b_2
a_1b_3	a_1b_4	a_2b_3	a_2b_4
a_3b_1	a_3b_2	a_4b_1	a_4b_2
a_3b_3	a_3b_4	a_4b_3	a_4b_4

 DeTensor

$a_1b_1 + a_2b_3$	$a_1b_2 + a_2b_4$
$a_3b_1 + a_4b_3$	$a_3b_2 + a_4b_4$

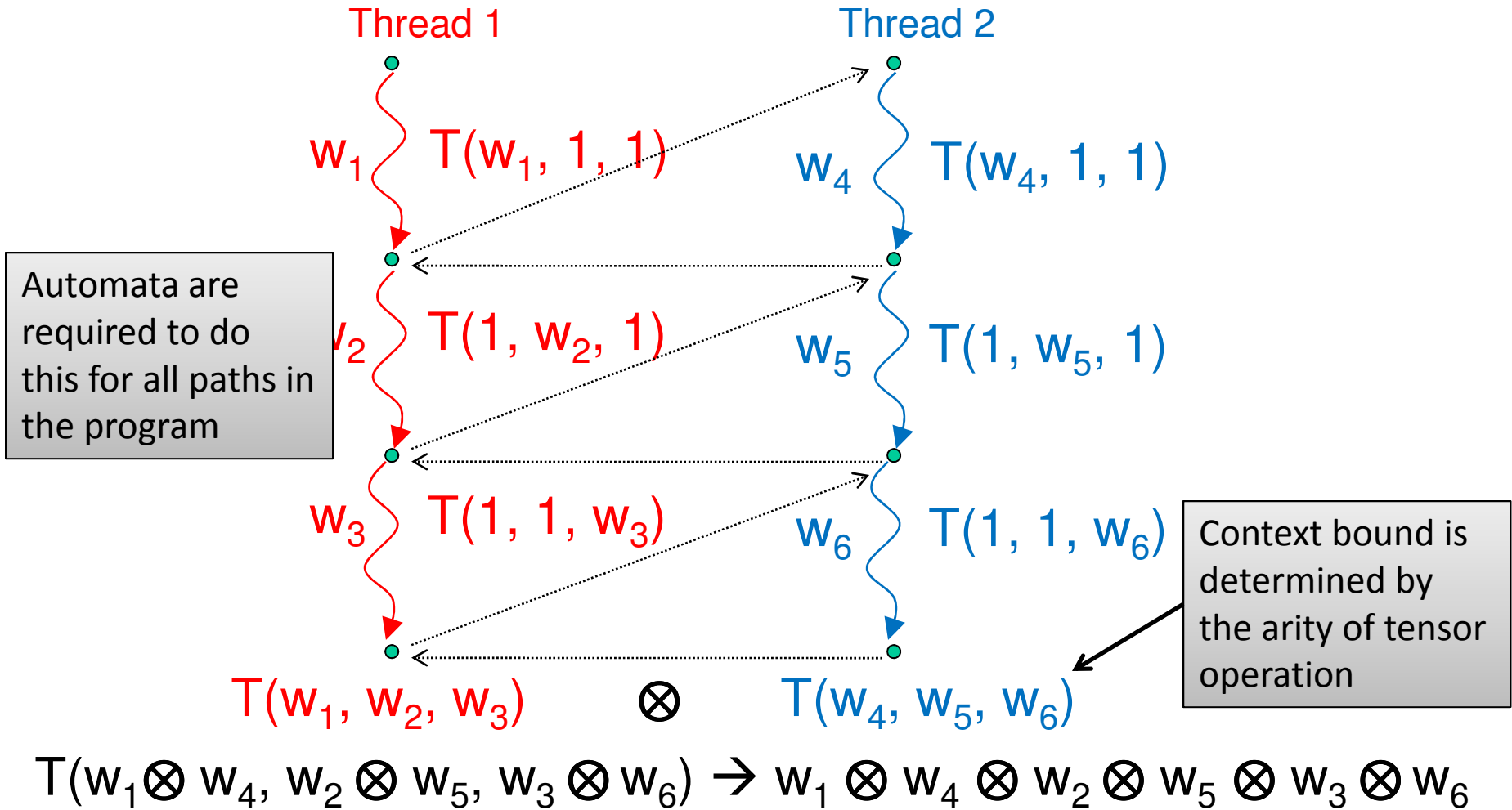
Tensors

- D is the set of matrices over a commutative domain
 - Finite relations (matrices over Booleans)
 - Affine relations (matrices over integers)
- Q: Does tensor product exist for all (bounded idempotent) semirings?

Part II: Context-Bounded Analysis

Tensors and Concurrency

Tensors give the necessary shuffling for interleaved executions

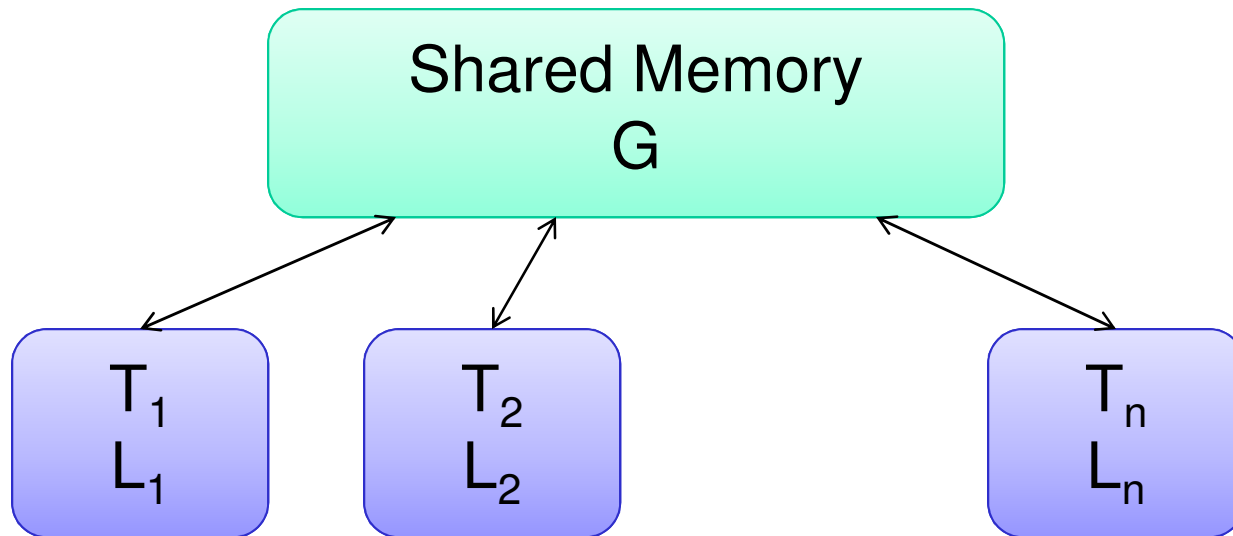


Application: Context-Bounded Analysis

- **Context Bounded Analysis:** interprocedural analysis of concurrent programs under a bound the number of context switches
- **Weighted Pushdown System:** A PDS with weights on rules.
 - Natural model for recursive programs
- **Theorem:** If all threads are modeled using WPDSs, and the weight domain has a tensor product, then for any bound K , one can precisely compute MOP.
 - Can solve reachability precisely
 - Can solve dataflow analysis precisely

Context-bounded analysis

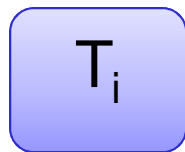
- Abstract model



$$G \times L_1 \times L_2 \times \dots \times L_n$$

Context-bounded analysis

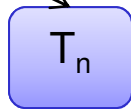
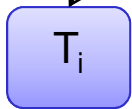
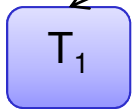
- Transition Systems



$$(g, l_i) \rightarrow_{T_i} (g', l_i')$$



$$(g, l_1, \dots, l_i, \dots, l_n) \Rightarrow_{T_i} (g', l_1, \dots, l_i', \dots, l_n)$$

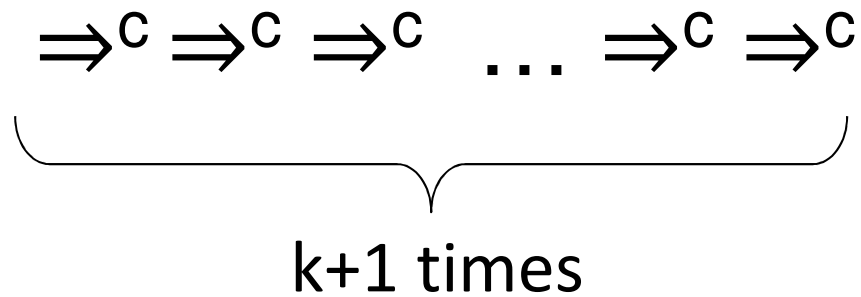


- Transition system for an execution context

$$\Rightarrow^c \text{ equals } \Rightarrow_{T_1}^* \cup \Rightarrow_{T_2}^* \cup \dots \cup \Rightarrow_{T_n}^*$$

Context-bounded analysis

- Want to check reachability in the transition system:



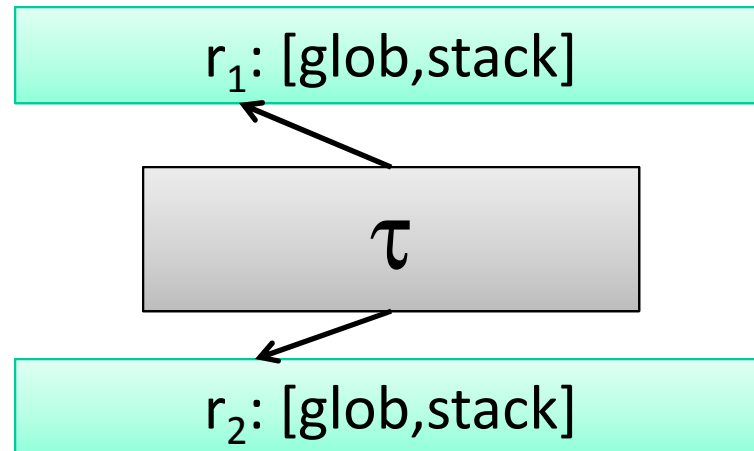
Thread Summarization

- In interprocedural analysis
 - Procedure re-analyzed for each input
 - Instead, one can build a summary
- We create a summary of an entire thread
 - Mapping starting states (input) to reachable states (output)
- **Transducers**: FSMs with an input and a output tape

Thread Summarization

- Reachability in a PDS can be modeled using a **transducer** [Caucal '92]

$(g_1, l_1) \rightarrow_T^* (g_2, l_2)$ iff $((g_1, l_1), (g_2, l_2)) \in L(\tau)$



- Advantage: transducers can be composed

$(r_1, r_2) \in L(\tau_1)$ and $(r_2, r_3) \in L(\tau_2)$ then $(r_1, r_3) \in L(\tau_1 ; \tau_2)$

Thread Summarization

For:	Construct:
$(g, l_i) \rightarrow_{T_i}^* (g', l_i')$	τ_i
$(g, l_1, \dots, l_i, \dots, l_n) \Rightarrow_{T_i}^*$ $(g', l_1, \dots, l_i', \dots, l_n)$	τ_i^e
\Rightarrow^c equals $\Rightarrow_{T_1}^* \cup \dots \cup \Rightarrow_{T_n}^*$	$\tau_c =$ $\tau_1^e \cup \tau_2^e \cup \dots \cup \tau_n^e$
$\Rightarrow^c \dots \Rightarrow^c \Rightarrow^c$	$\tau_c ; \dots ; \tau_c ; \tau_c$

Thread Summarization

- Context-bounded analysis reduces into a membership query on a transducer
- We'll extend these results to Weighted PDSs
 - Constructing weighted transducers
 - Composing weighted transducers
- Weighted Transducer: Given an input word s_1 , the transducer can write s_2 with a weight w (combine over all paths that write s_2)
 - $\tau(s_1, s_2) = w$

Thread Summarization

For:	Construct:
$(g, l_i) \rightarrow_{T_i}^* (g', l_i')$	τ_i [TACAS'08]
$(g, l_1, \dots, l_i, \dots, l_n) \Rightarrow_{T_i}^*$ $(g', l_1, \dots, l_i', \dots, l_n)$	τ_i^e
\Rightarrow^c equals $\Rightarrow_{T_1}^* \cup \dots \cup \Rightarrow_{T_n}^*$	$\tau_c =$ $\tau_1^e \cup \tau_2^e \cup \dots \cup \tau_n^e$
$\Rightarrow^c \dots \Rightarrow^c \Rightarrow^c$	$\tau_c ; \dots ; \tau_c ; \tau_c$

How Thread Summarization Works

- For a single thread:
 - $\tau_i(s_1, s_2) = \text{Reachable}(s_1, s_2)$
 - $\tau_i(s_1, s_2) = \text{MOP}(s_1, s_2)$
- Definition of composition
 - $\tau_3(s_1, s_2) = \bigvee_s \{ \tau_1(s_1, s) \wedge \tau_2(s, s_2) \}$
 - $\tau_3(s_1, s_2) = \bigoplus_s \{ \tau_1(s_1, s) \otimes \tau_2(s, s_2) \}$

- Consider the path:

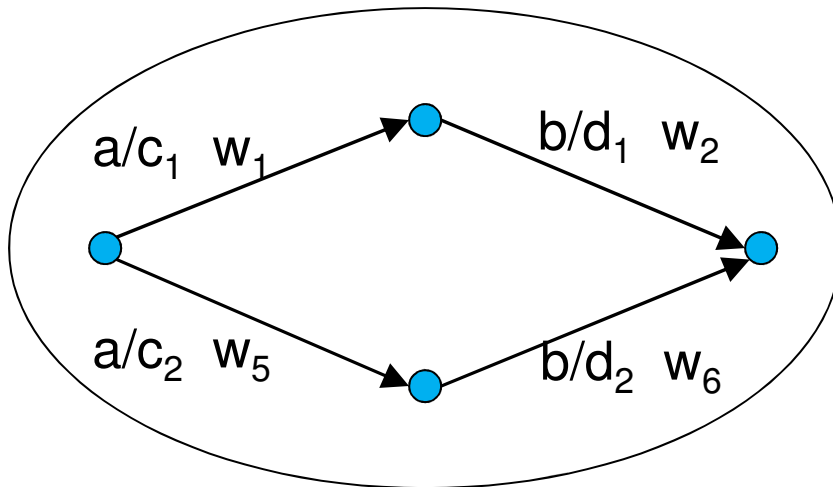
$$\underbrace{(g_1, l_1, l_2)}_{s_1} \xrightarrow{T_1^*} \underbrace{(g_2, l_1', l_2)}_s \xrightarrow{T_2^*} \underbrace{(g_3, l_1', l_2')}_{s_2}$$

$$\text{MOP}(s_1, s_2) = \bigoplus_s \tau_1(s_1, s) \otimes \tau_2(s, s_2)$$

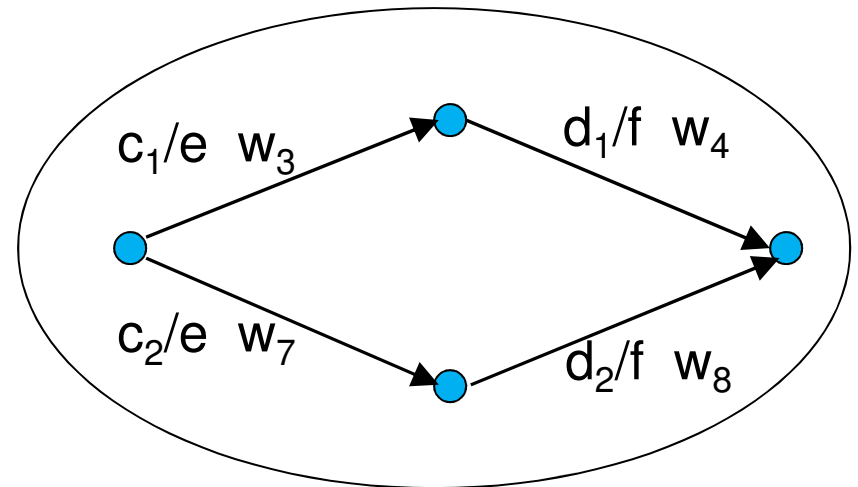
$$\tau_3(s_1, s_2)$$

Composing Transducers

- $\tau_3(s_1, s_2) = \bigoplus_s \{ \tau_1(s_1, s) \otimes \tau_2(s, s_2) \}$



$$\begin{aligned} ab &\rightarrow c_1d_1 & w_1 \otimes w_2 \\ ab &\rightarrow c_2d_2 & w_5 \otimes w_6 \end{aligned}$$

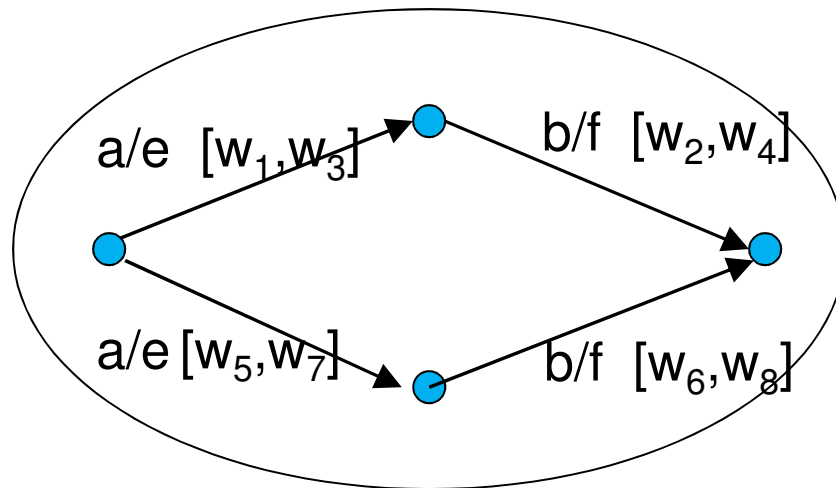
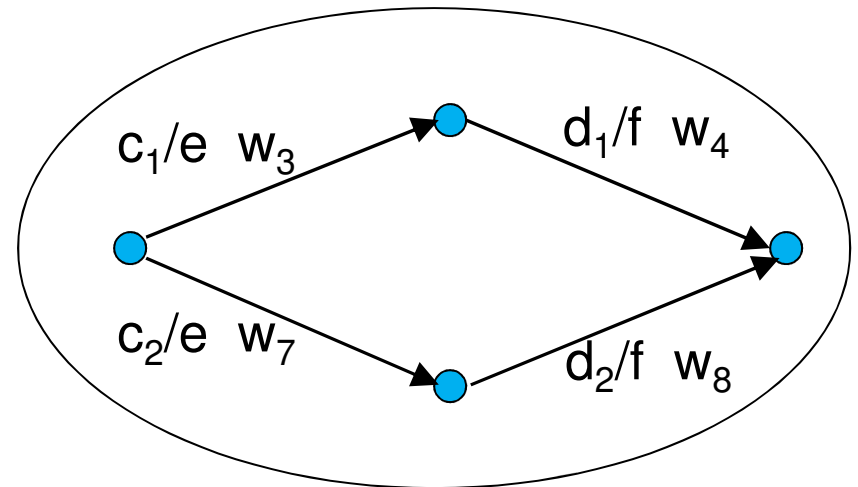
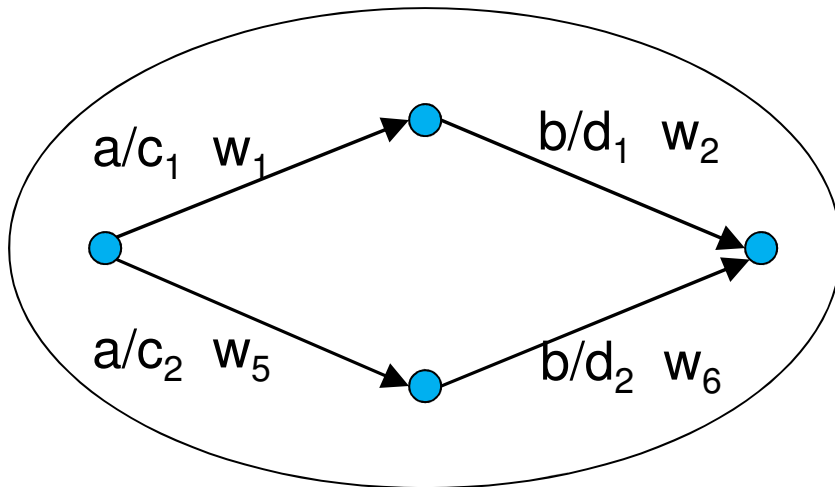


$$\begin{aligned} c_1d_1 &\rightarrow ef & w_3 \otimes w_4 \\ c_2d_2 &\rightarrow ef & w_7 \otimes w_8 \end{aligned}$$

$$\begin{aligned} ab &\rightarrow ef & w_1 \otimes w_2 \otimes w_3 \otimes w_4 \\ & & \oplus w_5 \otimes w_6 \otimes w_7 \otimes w_8 \end{aligned}$$

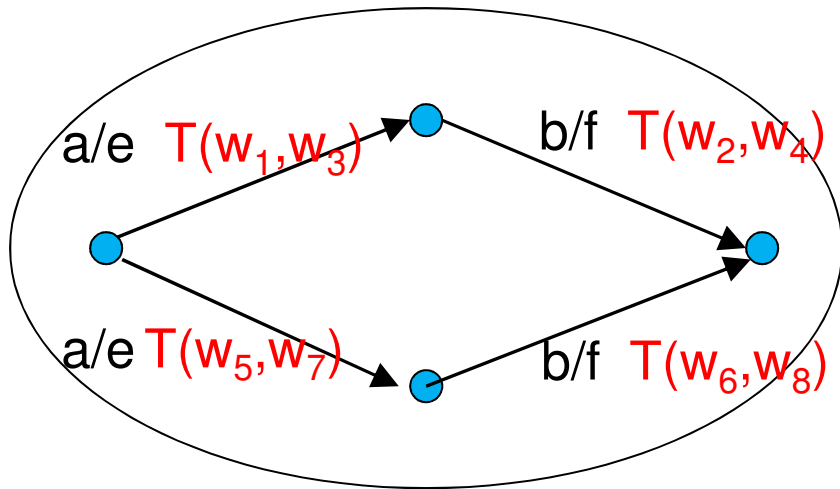
Composing Transducers

- $\tau_3(s_1, s_2) = \oplus_s \{ \tau_1(s_1, s) \otimes \tau_2(s, s_2) \}$



Composing Transducers

- $\tau_3(s_1, s_2) = \oplus_s \{ \tau_1(s_1, s) \otimes \tau_2(s, s_2) \}$



$$\begin{array}{c}
 T(w_1 \otimes w_2, w_3 \otimes w_4) \\
 \oplus T(w_5 \otimes w_6, w_7 \otimes w_8) \\
 \downarrow \text{DeTensor} \\
 \begin{array}{c}
 w_1 \otimes w_2 \otimes w_3 \otimes w_4 \\
 \oplus w_5 \otimes w_6 \otimes w_7 \otimes w_8
 \end{array}
 \end{array}$$

Summary

- We gave an algorithm for intersecting weighted automata
 - Extend need not be commutative
 - Requires tensor product for “shuffling”
- Generalizes to transducer composition
- Solves Context-Bounded Analysis