

# Notions of Opacity for Privacy and Security in Discrete Event Systems

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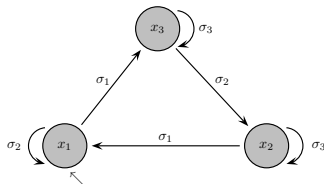
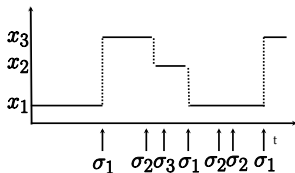
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# Introduction and Motivation

## Discrete Event (Dynamic) System (DES or DEDS)

- **Event-driven dynamics** [Cassandras and Lafortune, 2008]
  - 1 Numerous digital/cyberphysical systems are naturally event-driven (e.g., asynchronous distributed systems) or even exclusively event-driven (e.g., communication protocols)
  - 2 Event-driven sampling may be a design choice (e.g., [Branicky and Phillips, 2000], [Astrom and Bernhardsson, 2002], [Tabuada, 2007], [Dimarogonas et al, 2012], [Cassandras, 2015])
- **Discrete state space (typically)**
  - 1 Finite (e.g., finite automata) or infinite (e.g., unbounded Petri nets)
  - 2 Extensions to timed/stochastic/hybrid models (e.g., hybrid automata, continuous Petri nets)
  - 3 **Diverse levels of abstraction:** Logical, stochastic, hierarchical, ...

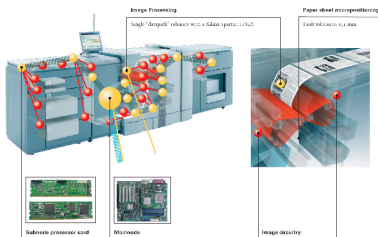


# Introduction and Motivation

## Application Domains ("Classical")

- **"Classical" Applications:** Manufacturing systems; baggage handling systems; paper handling systems (copiers, printers, etc.); heating, ventilation and air conditioning units

**Main characteristics and challenges:** **Model-based** (human designed), few (e.g., expensive) or unreliable sensors, different/complex modes of operation (e.g., monitoring vs testing), complexity of verification process



# Introduction and Motivation

## Emerging Application Domains

- **Emerging Applications:** Distributed (cyber-physical) systems, such as autonomous vehicles and automated highway systems; microgrids and smart grids; smart devices and buildings
- **New Features and Characteristics:**
  - **Distributivity/Modularity:** Multiple interacting (sub)systems, local observers and controllers
  - **Processing:** Local vs global, exchange of information
  - **Optimization:** Collaborative vs antagonistic strategies
  - **Communication:** Network delays, packet drops, synchronization
- **Privacy and Security Challenges:**
  - Shared (non-dedicated) communication infrastructures
  - Compromised components (e.g., sensors or actuators)
  - Curious or malicious actors (e.g., intruders)

# Opacity in Discrete Event Systems

## General (Behavioral) Description

- Certain critical system behavior deemed **secret** [Bryans et al., 2004] (described by **predicate** that evaluates to true or false)
- **Curious** observers (or passive intruders) are assumed to have
  - 1 Knowledge of a (possibly partial) model of the system
  - 2 Partial access to activity (observations) generated by the system
- Curious observers do **not** interfere with system operation in other ways (subsequent workshop talks address the effects of malicious intruders)
- **Opacity** requires the secret system behavior to remain opaque (uncertain) to passive intruders, under *all* system behavior
- Opaque system implies that the curious observer

never establishes that the predicate describing secret behavior is true
- Probabilistic extensions (more generally, ways of quantifying opacity) are also possible [Saboori and CNH, 2014]

# Opacity in Discrete Event Systems

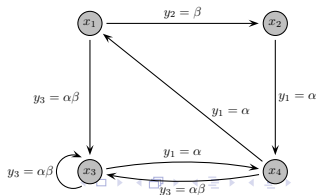
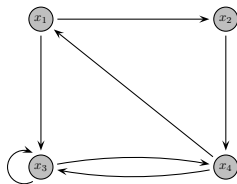
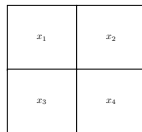
## Motivating Examples

- Motivating applications include assessment of
  - Monitoring limitations in sensor networks  
[Dubreil et al., 2010], [Saboori and CNH, 2011]
  - Encryption mechanisms based on pseudorandom generators  
[Saboori, 2011]
  - Protocols for privacy-preserving location-based services  
[Wu et al., 2014]
- Several existing security notions, such as [anonymity](#) and [noninterference](#), can also be described using opacity formulations

# Motivating Example I

## Monitoring Limitations in Sensor Networks

- Vehicle moves on a two-dimensional grid in which a number of sensors is deployed
- State of the vehicle corresponds to cell number of its location  $\Rightarrow$  Vehicle trajectory corresponds to state trajectory
- **Kinematic Model:** Automaton describing limitations on vehicle movements due to physical obstacles on the grid or other logical constraints or rules
- **Enhanced Kinematic Model:** Assign observation  $\sigma$  to all transitions that end in a cell covered by sensor  $\sigma$



# Motivating Example I

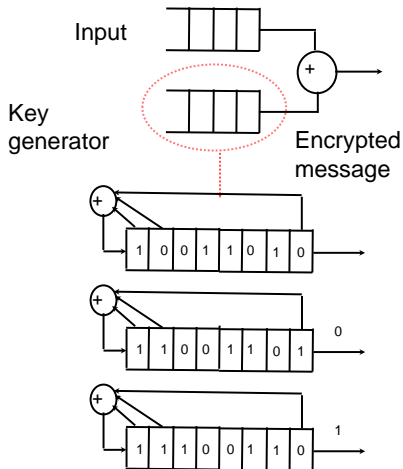
## Examples of Privacy/Security Concerns

- Can the origin of the vehicle be identified via observations from the sensor network (for all or some trajectories)?
- For such trajectories, how long (in the best/worst case) does it take for the sensor network to identify the origin?
- How fast does the number of consistent trajectories increase in terms of the length of the observation sequence?
- What sensor placement results in the tightest estimate of the vehicle state (either at present or at some point in the past) in the shortest time?
- What extra restrictions can we impose on vehicle movements in order to improve or impair our ability to localize the vehicle (i.e., perform state estimation) without changing sensor configuration?
- Assuming that some statistics about vehicle movements are known a priori, what is the most probable state of the vehicle along the observation?

# Motivating Example II

## Limitations of Encryption using Pseudorandom Generators

- Stream cipher: combines (usually through an XOR operation) plain text bits with a stream of keys
- LFSR-based stream cipher: Linear Feedback Shift Register creates a pseudorandom stream of keys
- An intruder can insert input bits and observe the encrypted message in an effort to obtain information about the system



# Motivating Example II

## Examples of Privacy/Security Concerns

- Is there an initial key (state) for which there exists an input sequence that reveals that key?
- If there is such a key, how long does it take for the intruder to detect it?
- Is there a (bad) sequence of key resets that aids the intruder in identifying the current (or previous) key faster?
- Assuming that some statistics about the initial key are known, what input sequence will reveal the key with the highest probability?

# Observability Related Challenges

DES Models and Property Verification [CNH, 2020]

## Common DES models:

- Finite automata, both deterministic and nondeterministic
- Petri nets, both bounded and unbounded
- Extensions: Timed models, stochastic models, hybrid models, ...  
Diverse levels of abstraction: Logical, stochastic, hierarchical, ...

## Sources of Uncertainty

- Common: initial state, partial event observation, nondeterminism
- Not-so-common: loss, delay, corruption of observations

## Opacity Specific Challenges:

- 1 Online algorithms for state estimation and event inference
- 2 Verification and complexity of opacity notions of interest
- 3 Automated tools for verifying/enforcing properties of interest

Recent book: CNH, *Estimation and Inference in Discrete Event Systems: A Model-Based Approach with Finite Automata*, Springer, 2020

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  - 1 Opacity as a privacy notion
  - 2 Motivating examples
- Observation Models; Language-Based and State-Based Opacity
- Current-State Opacity and its Verification
  - 1 Current-state estimation
  - 2 Formal definition of current-state opacity
  - 3 Verification using observer (current-state estimator)
- Initial-State Opacity and its Verification
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  - 3 Verification using initial-state estimator
- Other State-Based Notions of Opacity
- Ongoing Research and Challenges

# Nondeterministic Finite Automaton (NFA)

## Notation

$G = (X, \Sigma, \delta, X_0)$ , where

- $X$  is the set of states
- $\Sigma$  is the set of events
- $\delta : X \times \Sigma \rightarrow 2^X$   
nondeterministic transitions  
(Deterministic if  $|\delta(x, \sigma)| \leq 1$   
for all  $x \in X$  and  $\sigma \in \Sigma$ )
- $X_0 \subseteq X$  is the set of possible initial states

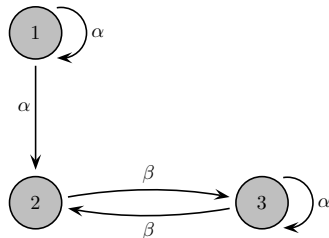
## Example NFA

$X = \{1, 2, 3\}$  and  $\Sigma = \{\alpha, \beta\}$

$X_0 = \{1, 2, 3\}$

For  $s = \alpha\beta\beta$ , we have

$\delta(\{1, 3\}, s) = \{2, 3\}$



Sequence of events:  $s = \sigma_{i_1}\sigma_{i_2}...\sigma_{i_k} \in \Sigma^*$  (of length  $|s| = k$ )

Behavior of  $G$  (language  $L(G)$ ):  $L(G) := \{s \in \Sigma^* \mid \exists x_0 \in X_0 \{\delta(x_0, s) \neq \emptyset\}\}$

Extended  $\delta$  function:  $\delta(X', \sigma) := \cup_{x' \in X'} \delta(x', \sigma)$  for  $X' \subseteq X$ ,  $\sigma \in \Sigma$   
 $\delta(x, \sigma s) := \delta(\delta(x, \sigma), s)$  for  $x \in X$ ,  $s \in \Sigma^*$ ,  $\sigma \in \Sigma$

# Observability Limitations

Unobservable Events ( $\Sigma_u$ ) and Observable Events ( $\Sigma_o$ )

- **Unobservable events**  $\Sigma_u$ ,  $\Sigma_u \subset \Sigma$ : Events whose occurrence goes unrecorded; remaining events  $\Sigma_o = \Sigma \setminus \Sigma_u$  are **observable**
- **Natural projection**  $P_{\Sigma_o} : \Sigma^* \rightarrow \Sigma_o^*$  (denoted by  $P$  when  $\Sigma_o$  is implied)  
Defined recursively  $\forall \sigma \in \Sigma, s \in \Sigma^*$

$$P(\epsilon) = \epsilon \text{ and } P(\sigma s) = P(\sigma)P(s)$$

where

$$P(\sigma) = \begin{cases} \sigma, & \text{if } \sigma \in \Sigma_o \\ \epsilon, & \text{otherwise} \end{cases}$$

- Natural projection “erases” all unobservable events in  $s$
- Event sequences compatible with sequence of observations  $\omega \in \Sigma_o^*$ :

$$P^{-1}(\omega) = \{s \in L(G) \mid P(s) = \omega\} \text{ (inverse projection, “explanations”)}$$

- **Generalizations** (not addressed here):
  1. Different events could generate identical observations (“labels”)
  2. Additional information (e.g., probabilistic information, time stamps)

# Notions of Opacity

Language-Based Opacity [Lin, 2011]

- Given NFA  $G = (X, \Sigma, \delta, X_0)$  with set of observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ )
- Curious observer with
  - (i) knowledge of system **model**  $G$  and
  - (ii) access to the sequence of **observations**  $\omega = P(s)$  (generated in response to sequence of events  $s$ ,  $s \in L(G)$ , acting in the system)
- Language-Based Opacity:**  $G$  is said to be opaque with respect to the **secret language**  $L_S$  ( $L_S \subset L(G)$ ) if

$\forall s \in L_S$ , we can find  $t \in (L(G) \setminus L_S)$ , such that  $P(s) = P(t)$
- Nomeclature:**  $L_S$  is the **secret** language, whereas  $L_{NS} = L(G) \setminus L_S$  is the **non-secret** language; intuitively, the curious observer should never know that the system has executed a secret sequence of events
- Extensions:**
  - Arbitrary non-secret language  $L_{NS}$  (not necessarily  $L(G) \setminus L_S$ )
  - Weak language-based opacity: we can find  $s \in L_S$  and  $t \in (L(G) \setminus L_S)$ , such that  $P(s) = P(t)$

# Notions of Opacity

State-Based Opacity [Saboori and CNH, 2007; 2009; 2011; 2013]

- Given NFA  $G = (X, \Sigma, \delta, X_0)$  with set of observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ )
- Curious observer with
  - knowledge of system **model**  $G$  and
  - access to the sequence of **observations**  $\omega = P(s)$  (generated in response to sequence of events  $s$ ,  $s \in L(G)$ , acting in the system)

- State-Based Opacity:**  $G$  is said to be (current-state) opaque with respect to the set of **secret states**  $S$  ( $S \subset X$ ) if

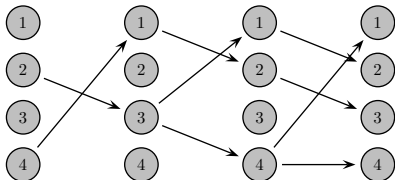
$\forall s \in L(G)$ , we can find  $t \in P^{-1}(s)$  such that  $\delta(X_0, t) \cap (X \setminus S) \neq \emptyset$

- Nomeclature:**  $S$  is the set of **secret** states, whereas  $NS = X \setminus S$  is the set of **non-secret** states; intuitively, the curious observer should never know with certainty that the system is in a secret state
- Extensions:
  - Arbitrary set of non-secret states  $NS$  (not necessarily  $X \setminus S$ )
  - Weak state-based opacity: there exists  $s \in L_S$ , for which we can find  $t \in P^{-1}(s)$  such that  $\delta(X_0, t) \cap (X - S) \neq \emptyset$

# State-Based Opacity

## Variations Based on Point in Time

- **Current-state opacity:** Entrance of current state to set of secret states  $S$  remains opaque
- **Initial-state opacity:** Membership of initial state to set of secret states  $S_0$  remains opaque during system operation
- Other opacity notions allow refinement of the observer estimate based on a subsequently observed sequence of observations (smoothing); these include  $K$ -step opacity, infinite-step opacity, etc.
- **Key challenge:** To verify (strong) opacity, we need to check these conditions for all possible sequences of observations



- $X = \{1, 2, 3, 4\}$
- State trajectories matching a sequence of 3 observations
- System is not initial-state opaque for  $S_0 = \{2, 4\}$
- System is not 2-step state opaque for  $S = \{1, 3\}$

# Verification of State-Based Opacity

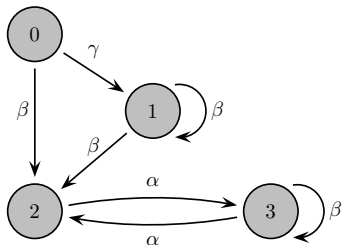
State Estimator Constructions [CNH, 2020]

- Given NFA  $G = (X, \Sigma, \delta, X_0)$  with set of observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ ) and a curious observer
- For regular languages, language-based and state-based opacity are **equivalent** within polynomial reduction [Wu and Lafortune, 2013]
- Verification of state-based opacity relies on different estimators
  - Current-state estimator (or observer)
  - Initial-state estimator
  - $K$ -step delayed estimator
  - Two-way observer
- Complexity depends on estimator complexity (typically, at least exponential in the size of  $G$ )
- More efficient verification may be possible in some cases

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# Current State Estimation

## Example of Recursive Computation of Possible Current States



- Consider NFA  $G$  given above with  $X_0 = \{0, 1, 2, 3\}$  and  $\Sigma_o = \{\alpha, \beta\}$
- Current state estimation:** Given a streaming sequence  $\omega \in \Sigma_o^*$ , track online possible current states  
 $\hat{X}(\omega) = \{x \in X \mid \exists x_0 \in X_0, \exists s \in \Sigma^* \text{ s.t. } P(s) = \omega \text{ and } x \in \delta(x_0, s)\}$

E.g., if we observe  $\omega = \alpha\beta\alpha$ , we can infer  $\hat{X}(\omega) = \{2\}$

Can recursively track possible current states ( $\Rightarrow$  online algorithm)

$$\left\{ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \end{array} \right\} \xrightarrow{\alpha} \left\{ \begin{array}{c} 2 \\ 3 \end{array} \right\} \xrightarrow{\beta} \{ 3 \} \xrightarrow{\alpha} \{ 2 \}$$

# Current State Estimation

## Formalizing Recursive Computation

- **Objective:** Following an **unknown** sequence of events  $s \in \Sigma^*$ , resulting in a sequence of observations  $\omega = P(s) \in \Sigma_o^*$ , obtain *current* state estimates, i.e.,

$$\hat{X}(\omega) = \{x \in X \mid \exists x_0 \in X_0, \exists s' \in \Sigma^* \text{ s.t. } P(s') = \omega \text{ and } x \in \delta(x_0, s')\}$$

- **Reachable set of states under a single observation:** For  $X' \subseteq X$ ,  $\sigma_o \in \Sigma_o \cup \{\epsilon\}$ , we let the set of states reachable from  $X'$  "via observation  $\sigma_o$ " (or "no observation" when  $\sigma_o = \epsilon$ ) be

$$R(X', \sigma_o) = \{x \in X \mid \exists x' \in X', \exists s \in \Sigma^* \text{ s.t. } P(s) = \sigma_o \text{ and } x \in \delta(x', s)\}$$

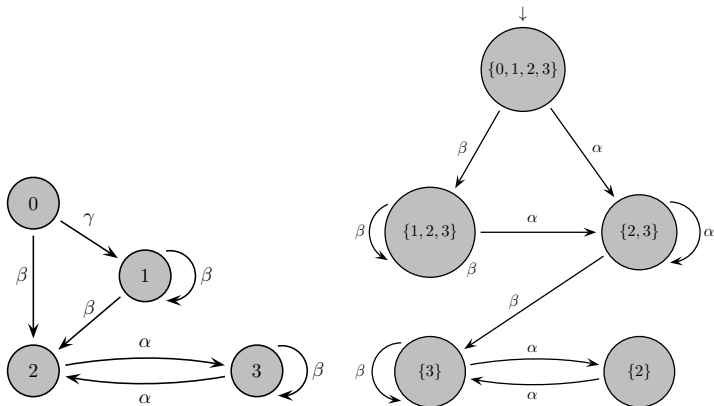
- Given  $\omega = \sigma_{i_1} \sigma_{i_2} \dots \sigma_{i_k} \in \Sigma_o^*$  and  $\sigma_{i_{k+1}} \in \Sigma_o$ , we can obtain the set  $\hat{X}$  recursively as

$$\begin{aligned}\hat{X}(\epsilon) &= R(X_0, \epsilon) \text{ "unobservable reach } UR(X_0) \\ \hat{X}(\omega \sigma_{i_{k+1}}) &= R(\hat{X}(\omega), \sigma_{i_{k+1}})\end{aligned}$$

- **Need:** Knowledge of system model or  $R(X', \sigma_o)$  for  $X' \subseteq X$  and  $\sigma_o \in \Sigma_o$

# Observer (Current-State Estimator) Construction

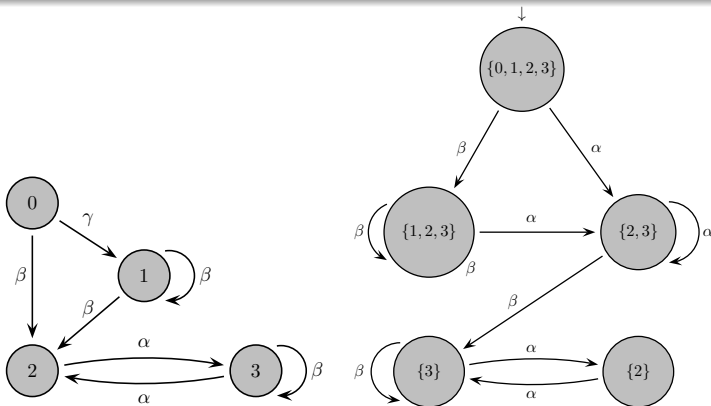
Tracking State Estimates Following *Any* Sequence of Observations



- Sequence of observations  $\alpha\beta\alpha$  leads us to state  $\{2\}$  (as seen earlier)

# Observer Limitations

No Tracking of State Sequences Following Sequences of Observations



- Sequences of states matching  $\beta\beta$  (which leads to  $\{1, 2, 3\}$ )

$0 \rightarrow 1 \rightarrow 1 \rightarrow 1$

$1 \rightarrow 1 \rightarrow 1$

$0 \rightarrow 1 \rightarrow 1 \rightarrow 2$

$1 \rightarrow 1 \rightarrow 2$

$3 \rightarrow 3 \rightarrow 3$

- Current-state estimator does **not** track state sequences

# Formal Construction of Observer

Determinizing an NFA [Cassandras and Lafortune, 2008]

- **Given:** NFA  $G = (X, \Sigma, \delta, X_0)$  with observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ )
- **Observer (or Current-State Estimator):** *Deterministic* finite automaton  $G_{obs} = (Q_{obs}, \Sigma_o, \delta_{obs}, Q_{0,obs})$  constructed as follows:
  - 1  $Q_{obs} \subseteq 2^X$ , i.e., each observer state  $q_{obs} \in Q_{obs}$  is associated with a unique subset of states of the given NFA  $G$ , i.e.,  $q_{obs} \subseteq X$
  - 2 Initial state is  $Q_{0,obs} = R(X_0, \epsilon)$  (unobservable reach of  $X_0$ )
  - 3 From any state  $q_{obs} \in Q_{obs}$  (recall  $q_{obs} \subseteq X$ ) of the current-state estimator, the next state for any  $\sigma_o \in \Sigma_o$  is given by

$$\delta_{obs}(q_{obs}, \sigma_o) = R(q_{obs}, \sigma_o)$$

- Observer captures the set of possible current states in  $G$  following a sequence of observations  $\omega \in \Sigma_o^*$  via

$$\hat{X}(\omega) = \delta_{obs}(Q_{0,obs}, \omega)$$

- **Note:** Observer **not** needed for online state estimation, but can be convenient for verification of certain properties (in some cases, verification may be possible via less complex constructions)

# Current-State Opacity

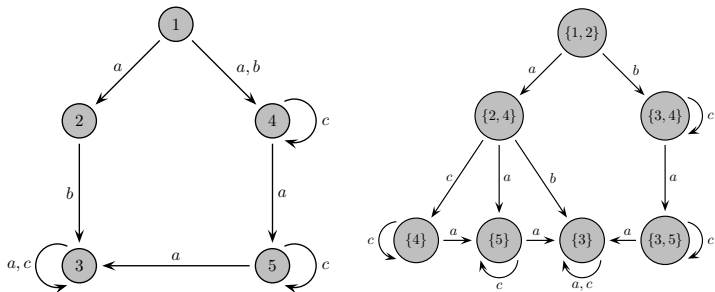
Formal Definition and Verification [Saboori and CNH, 2007, 2011]

- **Given:** NFA  $G = (X, \Sigma, \delta, X_0)$  with observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ ) and subset of secret states  $S$  ( $S \subseteq X$ )
- Current-state opacity requires that an external observer can never be certain that system state is within the set of secret states  $S$   
[At least one state outside  $S$  is possible; relates to “possible innocence” in anonymity protocols]
- **Current-state opacity [Saboori and CNH, 2007, 2011]:** For all  $s \in L(G)$ , for all  $x_0 \in X_0$  such that  $\delta(x_0, s) \neq \emptyset$ , it holds  $\{\delta(x_0, s) \subseteq S\} \Rightarrow \{\exists t \in \Sigma^*, \exists x'_0 \in X_0, \{P(t) = P(s), \delta(x'_0, t) \notin S\}\}$
- **Verification using an observer:**  $G$  is current-state opaque with respect to a set of secret states  $S$ ,  $S \subset X$ , if and only if

$$\forall q_{obs} \in Q_{obs}, \text{ we have } q_{obs} \cap (X \setminus S) \neq \emptyset$$

# Verification of Current-State Opacity

## Example

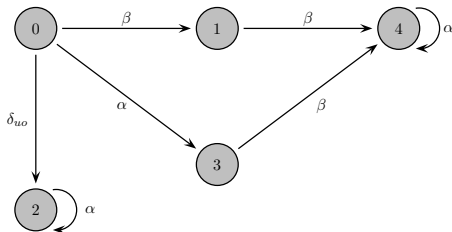


- $X_0 = \{1, 2\}$ ,  $\Sigma_o = \Sigma = \{a, b, c\}$
- Not current-state opaque wrt  $S = \{3\}$  or  $S = \{4\}$  or  $S = \{5\}$
- Current-state opaque wrt  $S = \{1\}$  or  $S = \{2\}$
- Consider  $S = \{4\}$ : sequence of observations  $ac$  reveals that current state is 4, however, remaining behavior is not opacity violating
- Enforcement of opacity via (i) appropriate control (**supervisory control**) or (ii) obfuscation of observations (**sensor manipulation**)

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# Initial State Estimation

## Example of Recursive Computation of Possible Initial States



- Consider NFA  $G$  with  $X_0 = \{0, 1, 2, 3, 4\}$  and  $\Sigma_o = \{\alpha, \beta\}$ ,  $\Sigma_u = \{\delta_{uo}\}$
- Initial state estimation:** Given a streaming sequence  $\omega \in \Sigma_o^*$ , track online possible initial states  
 $\hat{X}_0(\omega) = \{x_0 \in X_0 \mid \exists s \in \Sigma^* \text{ s.t. } P(s) = \omega \text{ and } \delta(x_0, s) \neq \emptyset\}$
- Key idea:** Track possible pairs  $(x_i, x_c)$  of an initial state  $x_i \in X_0$  and a *matching* current state  $x_c \in X$
- For example, if we observe  $\omega = \alpha\beta\alpha$ , we can recursively obtain

$$\left\{ \begin{array}{l} (0, 0) \\ (0, 2) \\ (1, 1) \\ (2, 2) \\ (3, 3) \\ (4, 4) \end{array} \right\} \xrightarrow{\alpha} \left\{ \begin{array}{l} (0, 2) \\ (0, 3) \\ (2, 2) \\ (4, 4) \end{array} \right\} \xrightarrow{\beta} \{ (0, 4) \} \xrightarrow{\alpha} \{ (0, 4) \}$$

# Initial-State Estimation Example

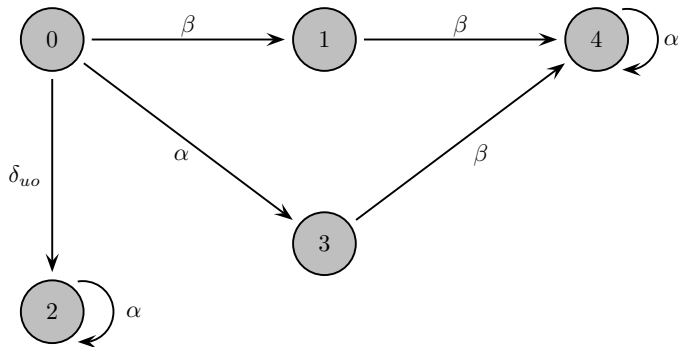
Tracking Initial State Estimates Following Sequences of Observations

Observation: Nothing

Matching Pairs of (Initial, Current) States:

$\{(0, 0), (0, 2), (1, 1), (2, 2), (3, 3), (4, 4)\}$

Initial State Estimate:  $\{0, 1, 2, 3, 4\}$



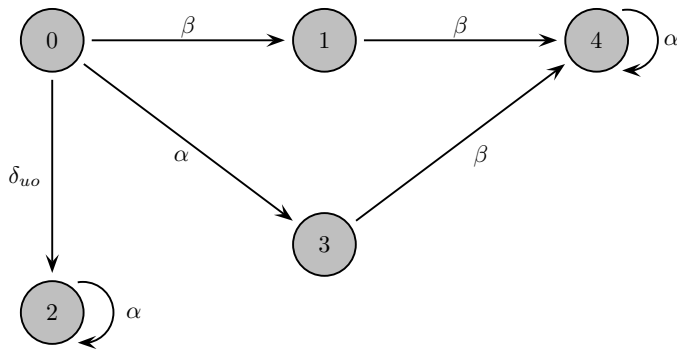
# Initial-State Estimation Example (2)

Tracking Initial State Estimates Following Sequences of Observations

Observation:  $\beta$

Matching Pairs of (Initial, Current) States:  $\{(0, 1), (1, 4), (3, 4)\}$

Initial State Estimate:  $\{0, 1, 3\}$



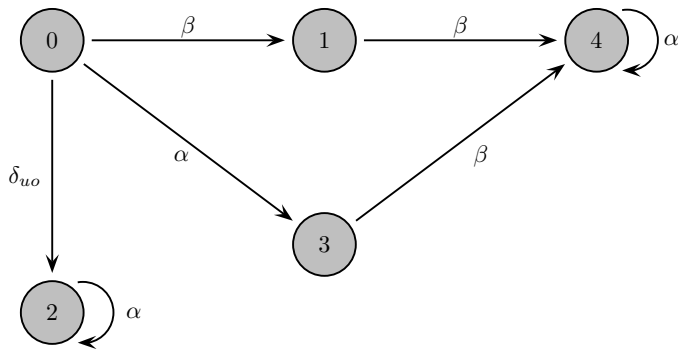
# Initial-State Estimation Example (3)

Tracking Initial State Estimates Following Sequences of Observations

Observation:  $\beta\beta$

Matching Pairs of (Initial, Current) States:  $\{(0, 4)\}$

Initial State Estimate:  $\{0\}$

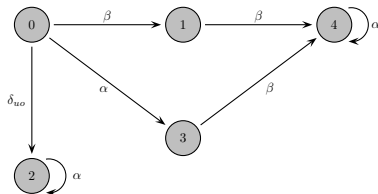


# Initial-State Estimator Construction

## Induced State Mappings and Composition

### System specifications:

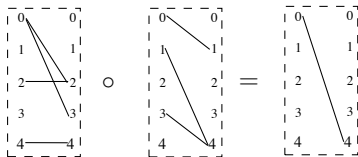
- $X_0 = X = \{0, 1, 2, 3, 4\}$
- $\Sigma = \{\alpha, \beta, \delta_{uo}\}$
- $\Sigma_u = \{\delta_{uo}\}$



### Induced State Mappings:

$$m_\alpha = \{(0, 2), (0, 3), (2, 2), (4, 4)\}$$

$$m_\beta = \{(0, 1), (1, 4), (3, 4)\}$$

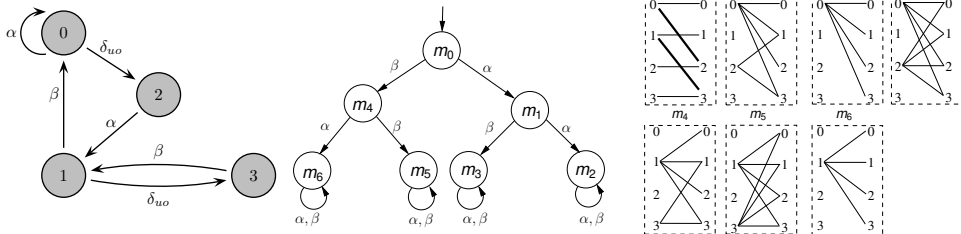


$m_{\alpha\beta}$  can be obtained via appropriate **composition** of  $m_\alpha$  and  $m_\beta$

$$m_{\alpha\beta} = \{(x_{i\alpha}, x_{c\beta}) \mid \exists x_{c\alpha} = x_{i\beta} \text{ s.t. } (x_{i\alpha}, x_{c\alpha}) \in m_\alpha \text{ and } (x_{i\beta}, x_{c\beta}) \in m_\beta\}$$

# Initial-State Estimator Construction

## Example



- ISE has  $O(2^{N^2})$  worst-case complexity ( $N = |X|$ )
- Can be used to determine both initial and current state  
E.g., if  $\beta\alpha(\alpha + \beta)^*$  is observed the initial state was 1, whereas current state could be any state in  $X$
- **Property:** Refinement of set of possible initial states as more observations become available

# Formal Construction of Initial-State Estimator

Tracking Pairs of Starting and Final States [Saboori and CNH, 2009; 2013]

- **Given:** NFA  $G = (X, \Sigma, \delta, X_0)$  with observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ )
- Let  $m_{\sigma_o} \subseteq X \times X$  denote the induced state mapping associated with  $\sigma_o$
- **Initial-State Estimator:** *Deterministic* finite automaton  $G_{iobs} = (Q_{iobs}, \Sigma_o, \delta_{iobs}, Q_{0,iobs})$  constructed as follows:
  - 1  $Q_{iobs} \subseteq 2^{X \times X}$ , i.e., each initial-state estimator state  $q_{iobs} \in Q_{iobs}$  is associated with a unique subset of pairs of states of the form  $(x_i, x_c)$  where  $x_i$  is a possible initial state and  $x_c$  is a corresponding possible current state
  - 2 Initial state is  $Q_{0,iobs} = \bigcup_{x_0 \in X_0} \{\{x_0\} \times R(x_0, \epsilon)\}$  (each  $x_0 \in X_0$  is paired with all states in  $R(x_0, \epsilon)$  that can be reached from  $x_0$  via zero, one, or more unobservable transitions)
  - 3 From any state  $q_{iobs} \in Q_{iobs}$  (recall  $q_{iobs} \subseteq X \times X$ ) of the initial-state estimator, the next state for any  $\sigma_o \in \Sigma_o$  is captured by

$$\delta_{iobs}(q_{iobs}, \sigma_o) = q_{iobs} \circ m_{\sigma_o}$$

- Initial-state estimator captures the set of possible initial states in  $G$  following a sequence of observations  $\omega \in \Sigma_o^*$  via

$$\hat{X}_0(\omega) = \{x_i \in X_0 \mid (x_i, x_c) \in \delta_{iobs}(Q_{0,iobs}, \omega)\}$$

# Initial-State Opacity

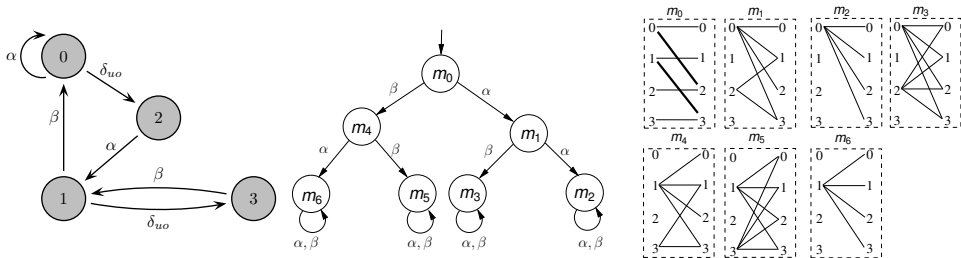
Formal Definition and Verification [Saboori and CNH, 2008]

- **Given:** NFA  $G = (X, \Sigma, \delta, X_0)$  with observable events  $\Sigma_o$  ( $\Sigma_o \subseteq \Sigma$ ) and subset of secret states  $S_0$  ( $S_0 \subseteq X_0$ )
- Initial-state opacity requires that an external observer can never be certain that system initial state is within the set of secret initial states  $S_0$   
[For all observation sequences, at least one state outside  $S_0$  is possible]
- **Initial-State Opacity [Saboori and CNH, 2008]:** For all  $s \in L(G)$ , for all  $x_0 \in S_0$ , it holds  
 $\{\delta(x_0, s) \neq \emptyset\} \Rightarrow \{\exists t \in \Sigma^*, \exists x'_0 \in (X_0 \setminus S_0), \{P(t) = P(s), \delta(x'_0, t) \neq \emptyset\}\}$
- Verification using an **initial-state estimator**  
 $G_{iobs} = (Q_{iobs}, \Sigma_o, \delta_{iobs}, Q_{0,iobs})$
- For  $q_{iobs} \in Q_{iobs}$ , let  $I(q_{iobs}) = \{x_i \in X_0 \mid (x_i, x_c) \in q_{iobs}\}$ ;  $G$  is initial-state opaque if and only if

$\forall q_{iobs} \in Q_{iobs}$ , we have  $I(q_{iobs}) \cap (X_0 \setminus S_0) \neq \emptyset$

# Verification of Initial-State Opacity

## Example



- Not initial-state opaque wrt  $S_0 = \{0\}$  (e.g.,  $\alpha\alpha(\alpha + \beta)^*$  reveals initial state was 0)
- Not initial-state opaque wrt  $S_0 = \{1\}$  (e.g.,  $\beta\alpha(\alpha + \beta)^*$  reveals initial state was 1)
- Initial-state opaque wrt  $S_0 = \{2\}$  or  $S_0 = \{3\}$  or  $S_0 = \{2, 3\}$
- Enforcement of initial-state opacity via (i) appropriate control (supervisory control) or (ii) obfuscation of observations (sensor manipulation)

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# Recursive State Estimation

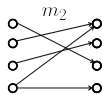
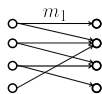
State Mappings, Composition, Concatenation [CNH, 2020]

- A **state mapping**  $m \subseteq X \times X$  contains pairs of the form  $(x_{i_1}, x_{i_2})$  where  $x_{i_1}$  ( $x_{i_2}$ ) can be thought as current (next) state
- State mappings  $m_1, m_2 \subseteq X \times X$  can be composed (to generate a new state mapping) or concatenated (to generate a trellis diagram) as

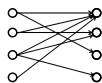
$$m_1 \circ m_2 = \{(x_{i_1}, x_{i_3}) \mid \exists x_{i_2} \in X \text{ s.t. } (x_{i_1}, x_{i_2}) \in m_1 \text{ and } (x_{i_2}, x_{i_3}) \in m_2\}$$

$$m_1 \bullet m_2 = \{(x_{i_1}, x_{i_2}, x_{i_3}) \mid \exists (x_{i_1}, x_{i_2}) \in m_1, (x_{i_2}, x_{i_3}) \in m_2\}$$

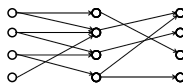
- Graphical depiction of **composition** and **concatenation** (arrows connect a state  $x_{i_1} \in X$  with another state  $x_{i_2} \in X$ )



Composition  
 $m_1 \circ m_2$



Concatenation  
 $m_1 \bullet m_2$



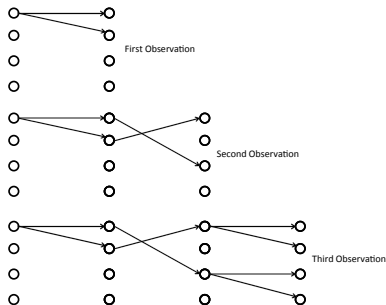
# Recursive State Estimation

## Output State Mappings and Induced Trellis Diagrams

- Each observable event  $\sigma_o \in \Sigma_o$  can be associated with a **state mapping**

$$m_{\sigma_o} = \{(x_c, x_n) \mid \exists s \in \Sigma^* \text{ s.t. } P(s) = \sigma_o \text{ and } x_n \in \delta(x_c, s)\}$$

- State mappings corresponding to a sequence of observable events,  $\omega = \sigma_{i_1} \sigma_{i_2} \dots \sigma_{i_k} \in \Sigma_o^*$  can be concatenated as  $m_{\sigma_{i_1}} \bullet m_{\sigma_{i_2}} \bullet \dots \bullet m_{\sigma_{i_k}}$
- Resulting construction captures matching **sequences of states**

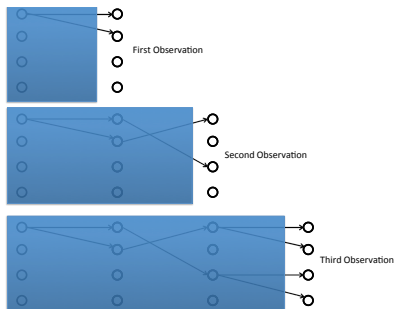


- Arrows represent (possibly different) sequences of events that generate the observation at the corresponding stage

# Current State Estimation

## Pruning of Trellis Diagrams

- Trellis diagrams can be pruned from parts not useful for task at hand
- Current state estimation only needs latest stage

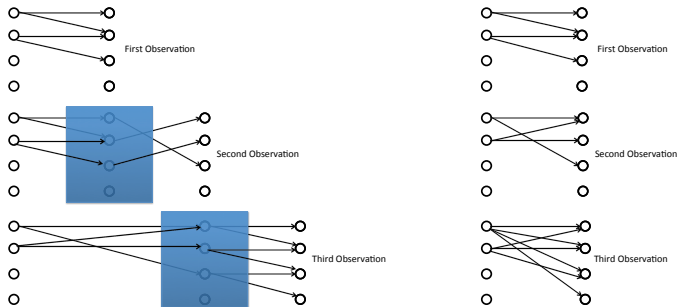


- Results in earlier recursive current state estimation procedure
- One can also annotate possible current states with additional information (e.g., *a posteriori* probabilities for current states)

# Initial State Estimation

## Pruning of Trellis Diagram

- Initial state estimation only needs **initial** stage and **latest** stage



- Reduced construction (on the right) captures earlier recursive initial state estimation procedure
- Again, one can annotate possible initial/current states with additional information (e.g., *a posteriori* probabilities for initial states)

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# Opacity in DES

## Ongoing Research and Current Challenges

- **Extensions to other DES:**
  - 1 Petri net models (and other purely event-driven systems)
  - 2 Stochastic systems (stochastic notions of opacity)
  - 3 Timed systems (timed notions of opacity)
- **Extensions to Cyberphysical systems:**
  - 1 Quantifying opacity (measures for opacity)
  - 2 Appropriate notions of opacity and their verification
- **Extensions to distributed/decentralized observation settings**
  - 1 Role of modularity and/or other system structure
  - 2 Resiliency to transmission delays, packet drops, errors in communication exchanges, faulty/malicious components
- **Opacity Enforcement Strategies**
  - 1 Supervisory control
  - 2 Obfuscation
  - 3 Game Formulations

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