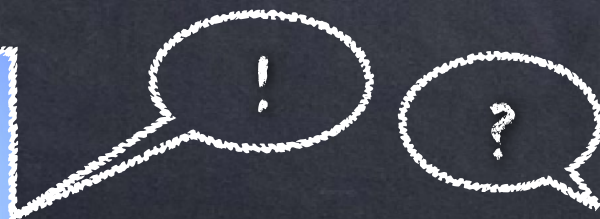


Inferring Symbolic Automata

Hadar Frenkel

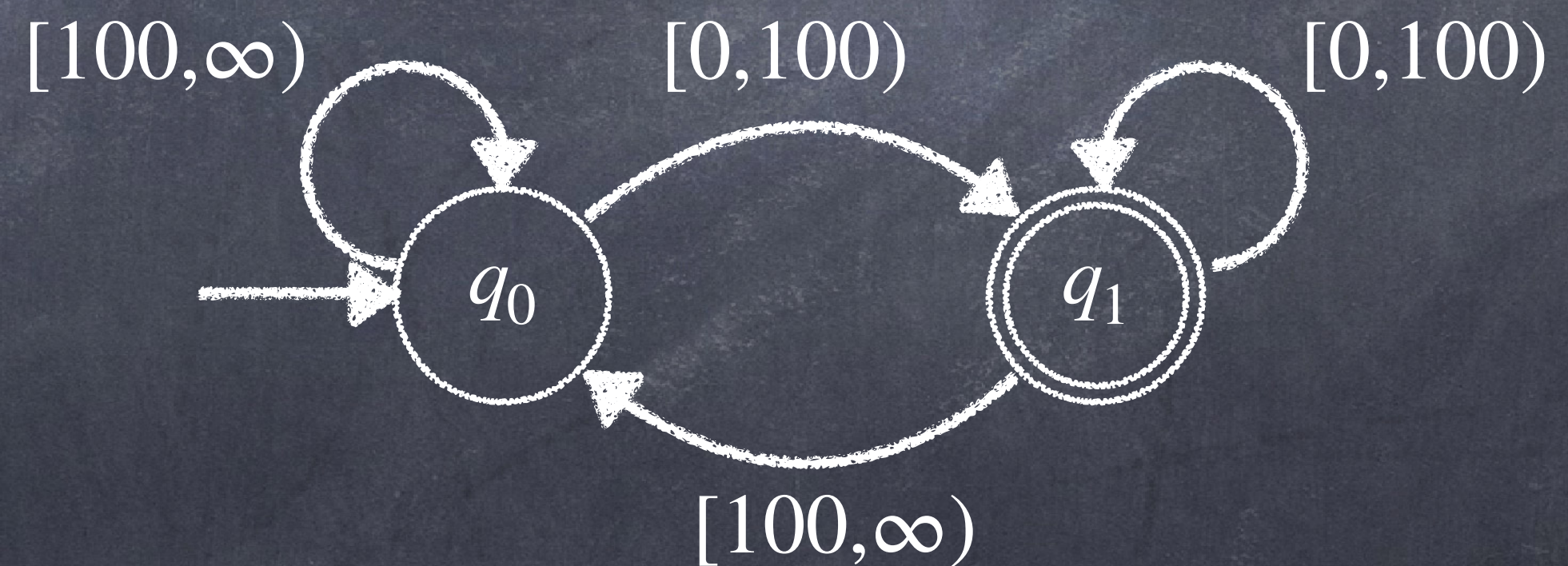
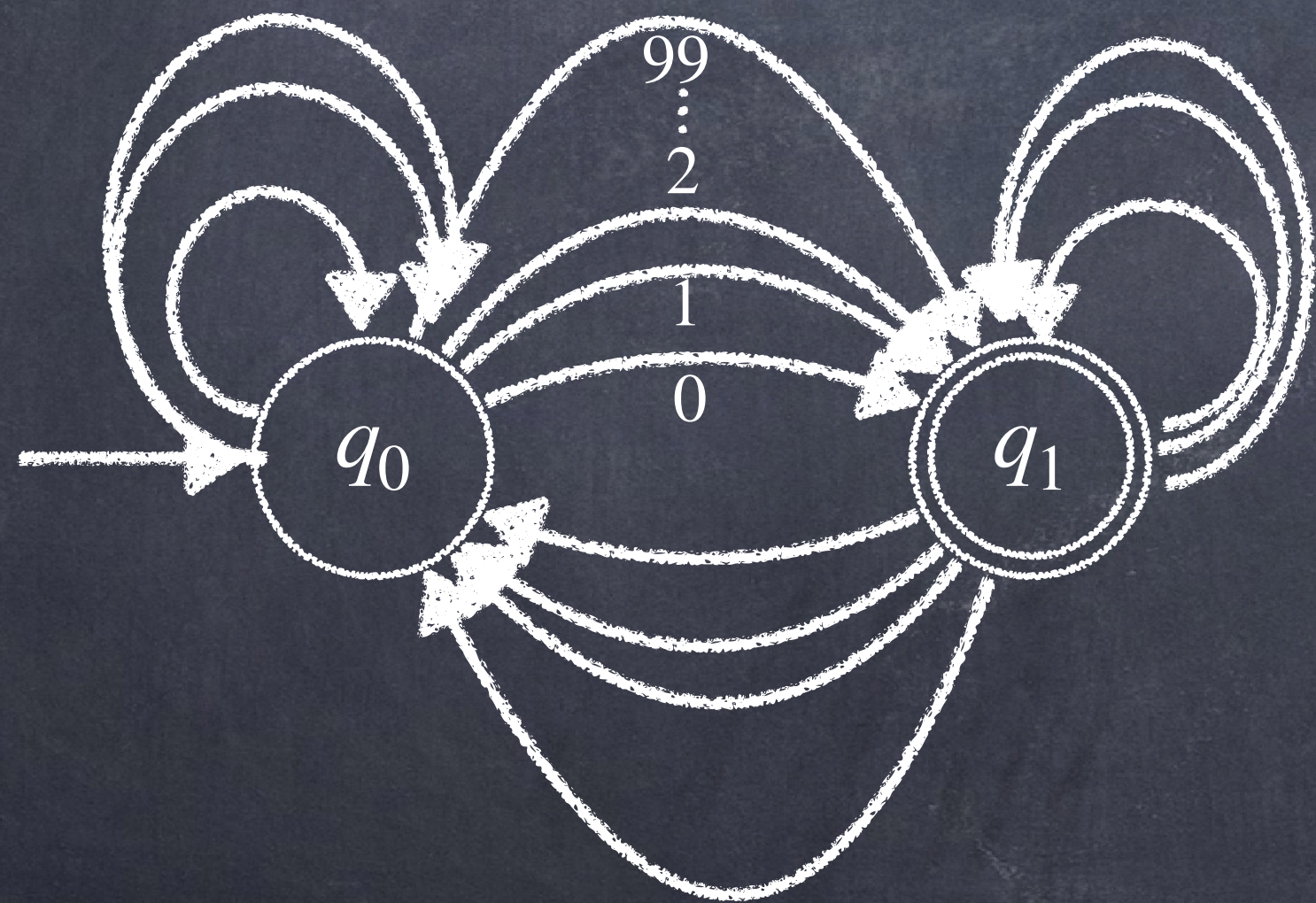
CISPA Helmholtz Center for Information Security, Saarbrücken, Germany

Joint work with Dana Fisman and Sandra Zilles



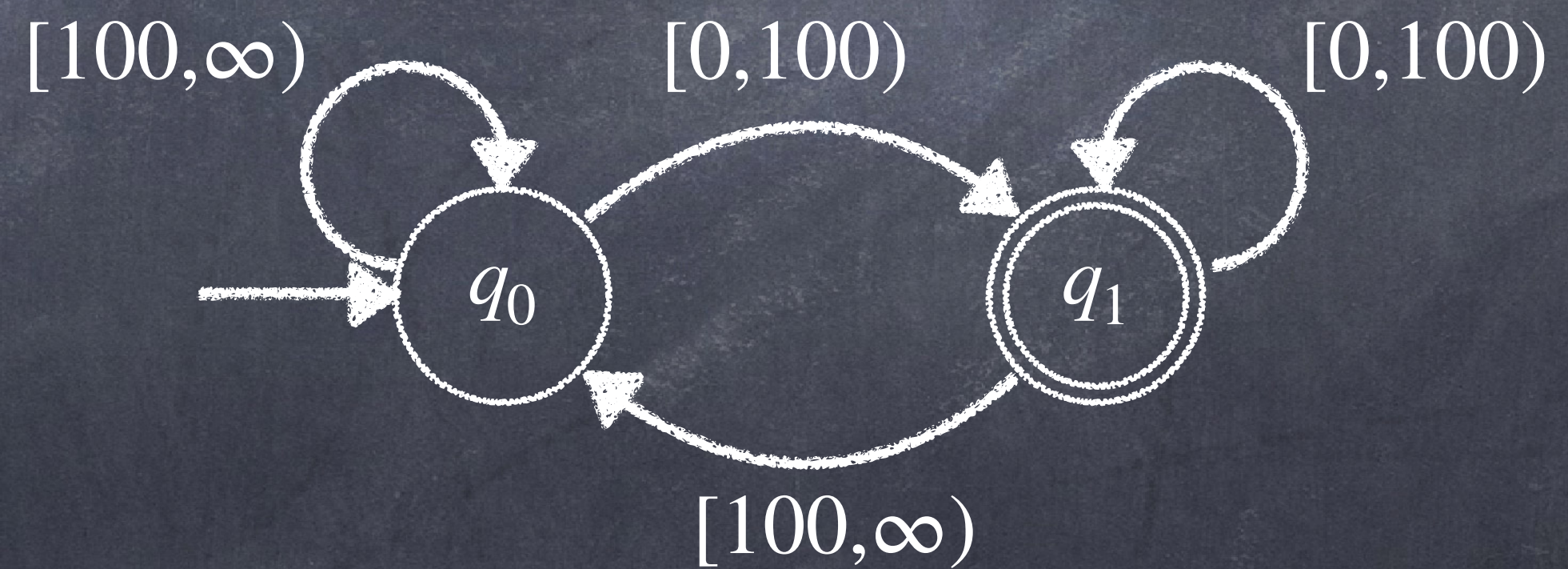
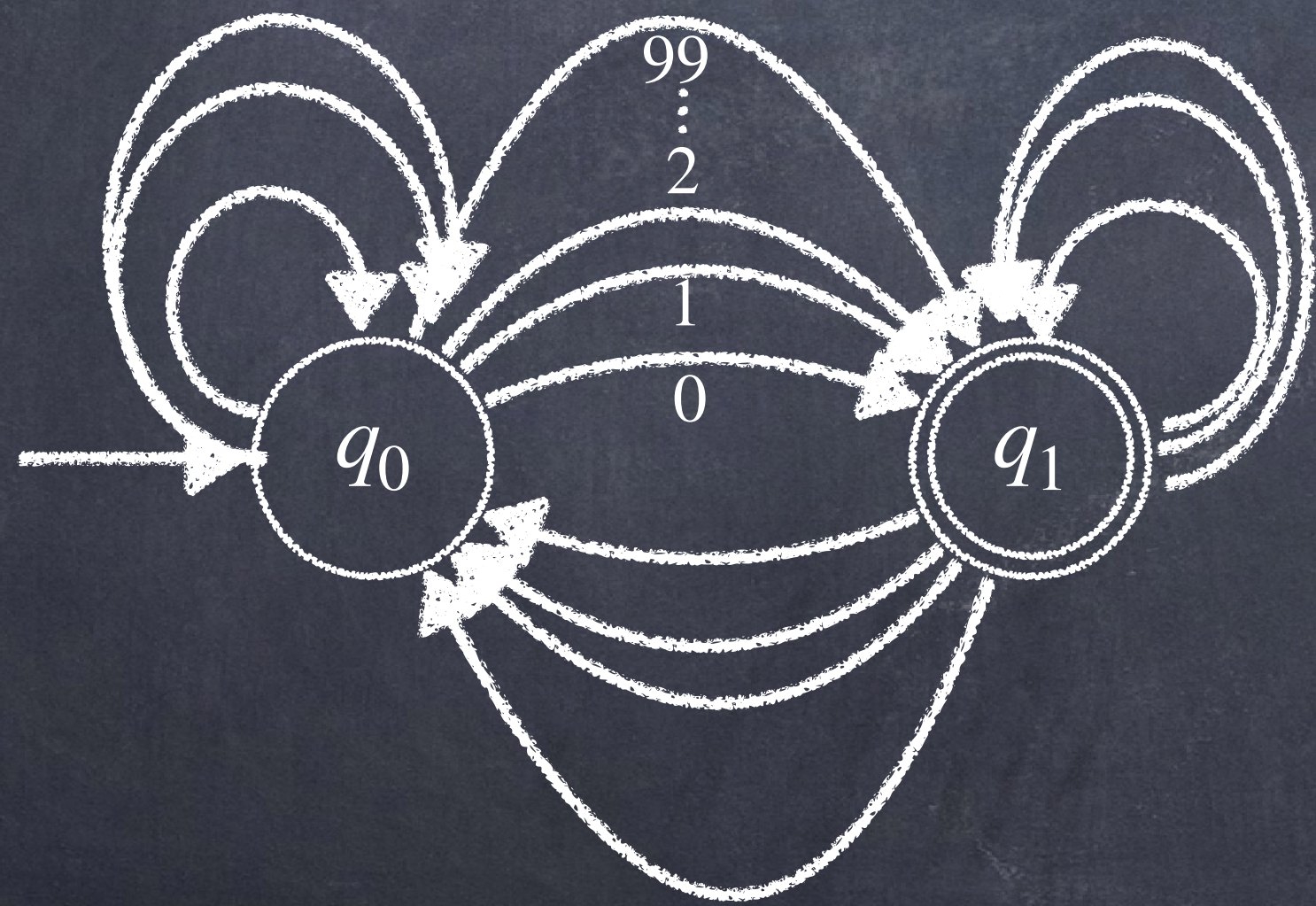
Symbolic Automata — SFAs

- Finite state automata
- Defined w.r.t. a Boolean algebra
- Transitions are over predicates



Symbolic Automata — SFAs

- Finite state automata
- Defined w.r.t. a Boolean algebra
- Transitions are over predicates
- Concise
- Reason about infinite domains



Monotonic Algebras

- Predicates correspond to a total order over the domain elements
- $[\psi] = \{d \mid a \leq d \leq b\}$
- Monotonic: Interval algebras (over $\mathbb{N}, \mathbb{Z}, \mathbb{R}$)



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Propositional algebra

- Predicates are Boolean combinations of atomic propositions
- $(p_1 \wedge p_2) \vee (\neg p_1 \wedge p_3)$
- Not monotonic!

Automata Learning

- Active Learning - L^* style Learning [Angluin 1987]

- Passive Learning

Automata Learning

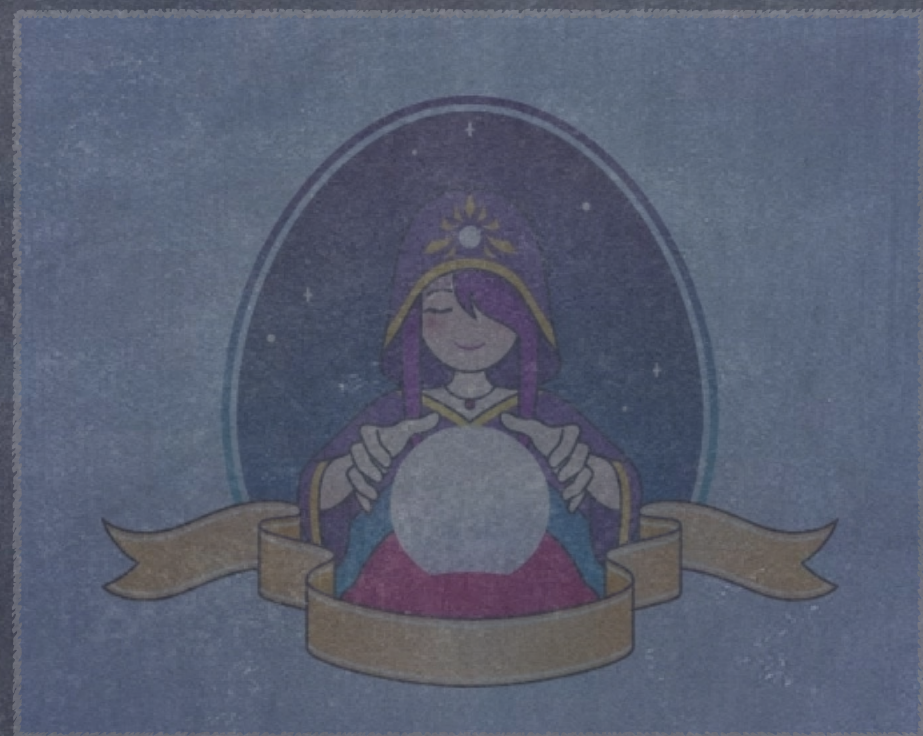
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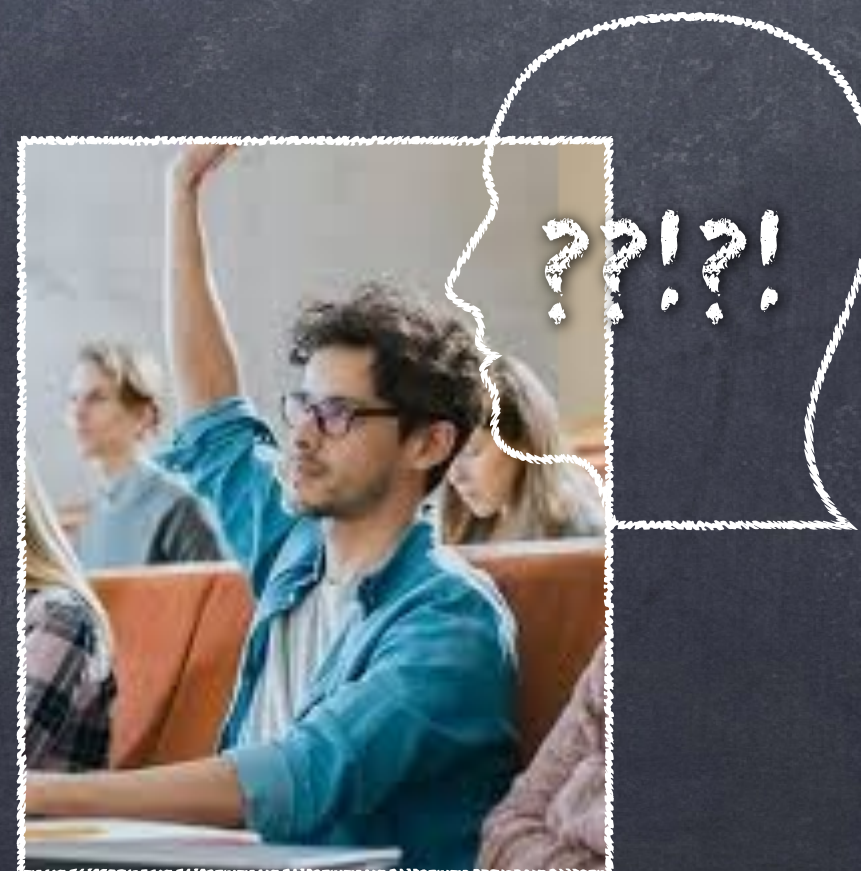
Automata Learning

- Active Learning - L^* style Learning [Angluin 1987]



- Passive Learning

$\langle w_1, \perp \rangle$
 $\langle w_2, \top \rangle$
⋮
 $\langle w_n, \perp \rangle$



Learnability of a Class of Languages via Representation \mathcal{R}

- Different representations of languages

- E.g. regular languages — DFAs, NFAs

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- E.g. L^* algorithm for regular languages via representation in DFAs

Active Learning of SFAs

- Positive results
 - Learning of SFAs over monotonic algebras using membership and equivalence queries
 - [Maler & Mens 2014], [Maler & Mens 2017]
 - [Chubachi, Diptarama, Yoshinaka, Shinohara 2017]
 - MAT* algorithm for learning SFAs
 - [Argyros & D'Antoni 2018]





Active Learning of SFAs

- First negative result





Active Learning of SFAs

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- Necessary condition:
- We can **polynomially learn SFAs** over a Boolean algebra \mathcal{A} using membership and equivalence queries only if we can **polynomially learn the predicates** of \mathcal{A} using membership and equivalence queries





Active Learning of SFAs

- First negative result
- Necessary condition:
- We can **polynomially learn SFAs** over a Boolean algebra \mathcal{A} using membership and equivalence queries only if we can **polynomially learn the predicates** of \mathcal{A} using membership and equivalence queries

→ SFAs over the propositional algebra are not polynomially learnable



Passive Learning



set
 S'

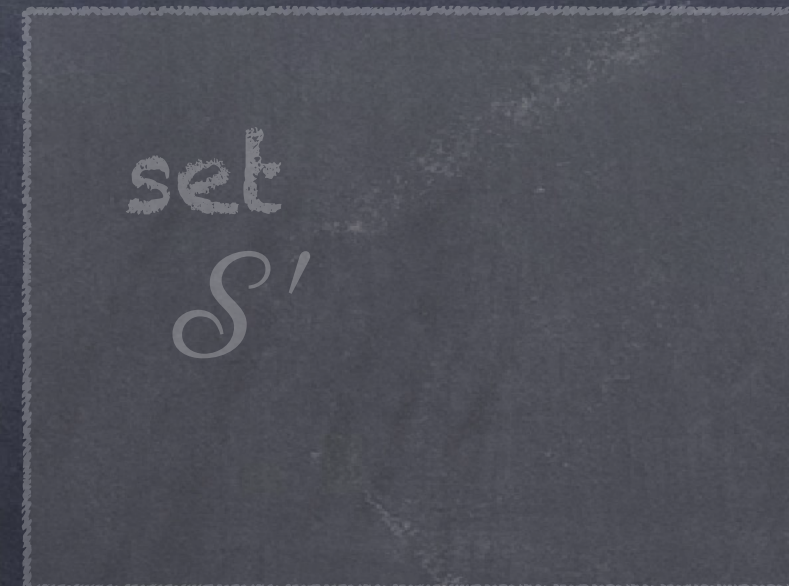
Infer →



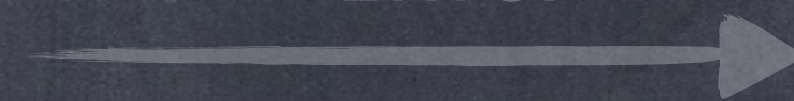
Identification in the Limit Using Polynomial Time and Data



Characteristic



Infer



Identification in the Limit Using Polynomial Time and Data



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Infer



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Infer



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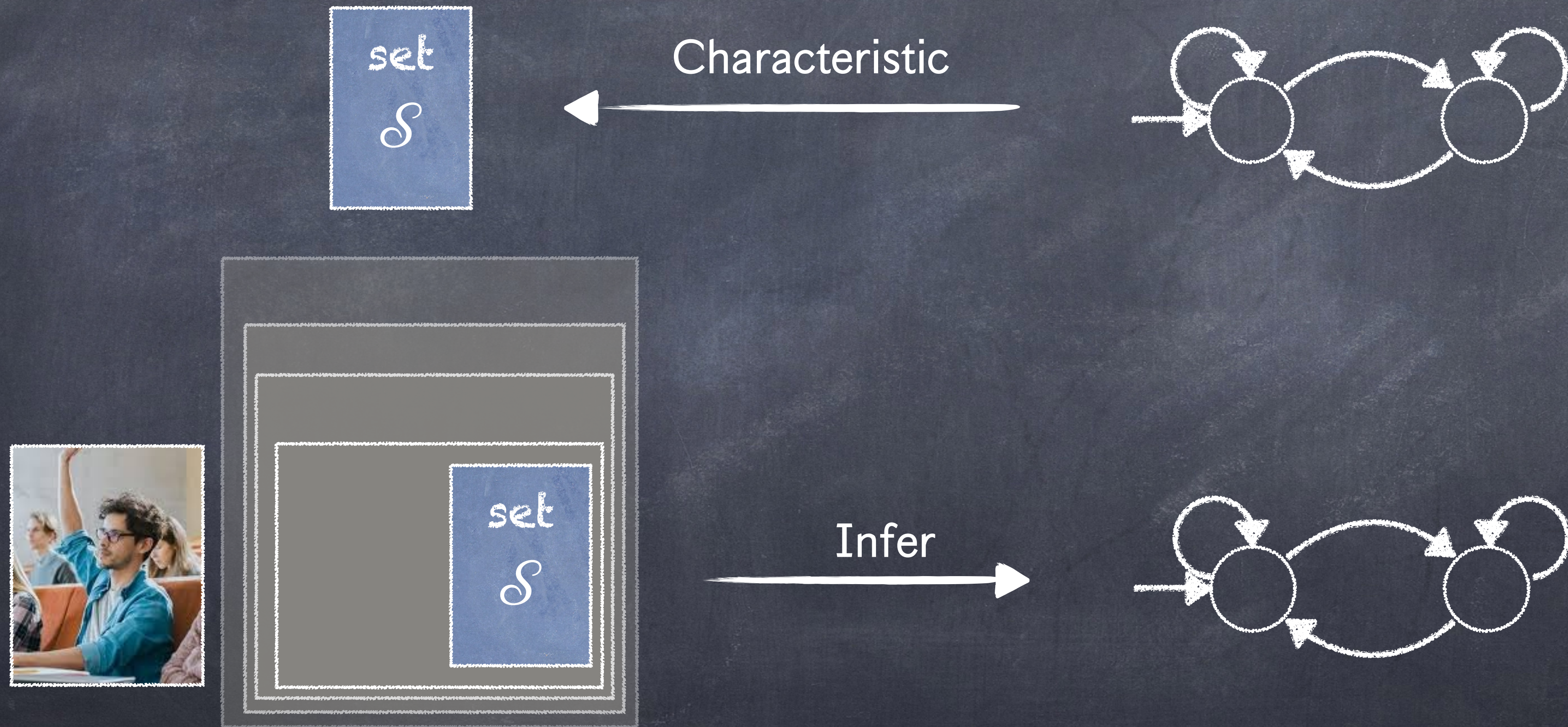
Characteristic



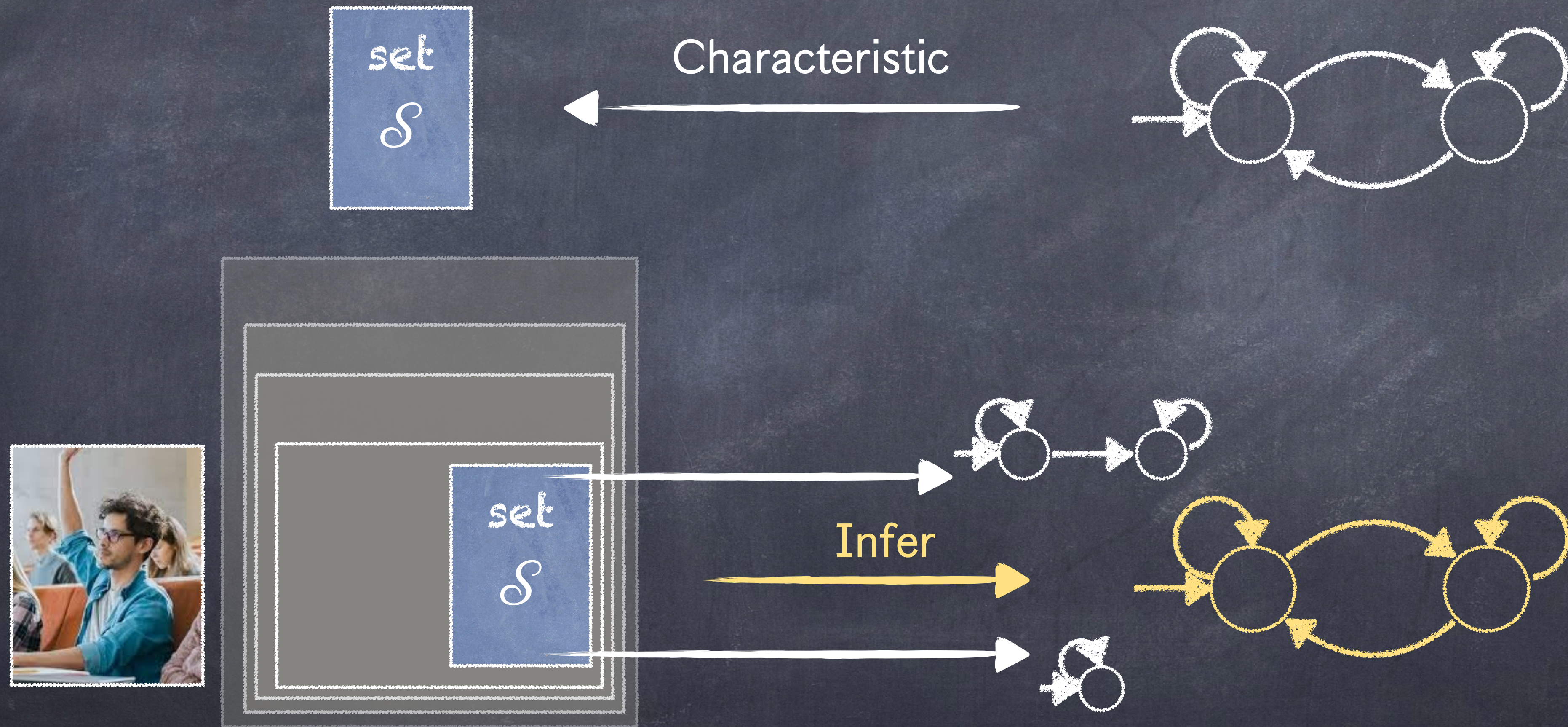
Infer



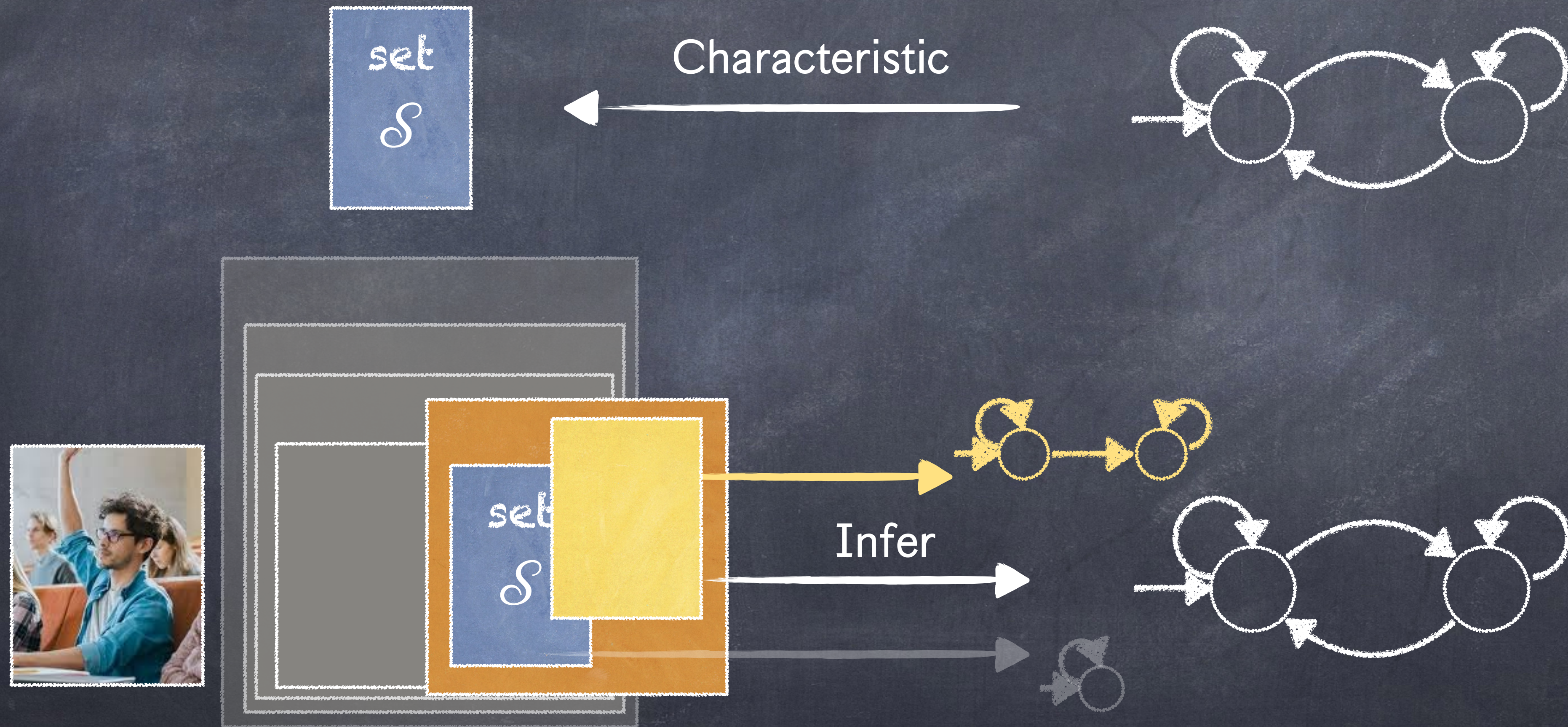
Identification in the Limit Using Polynomial Time and Data



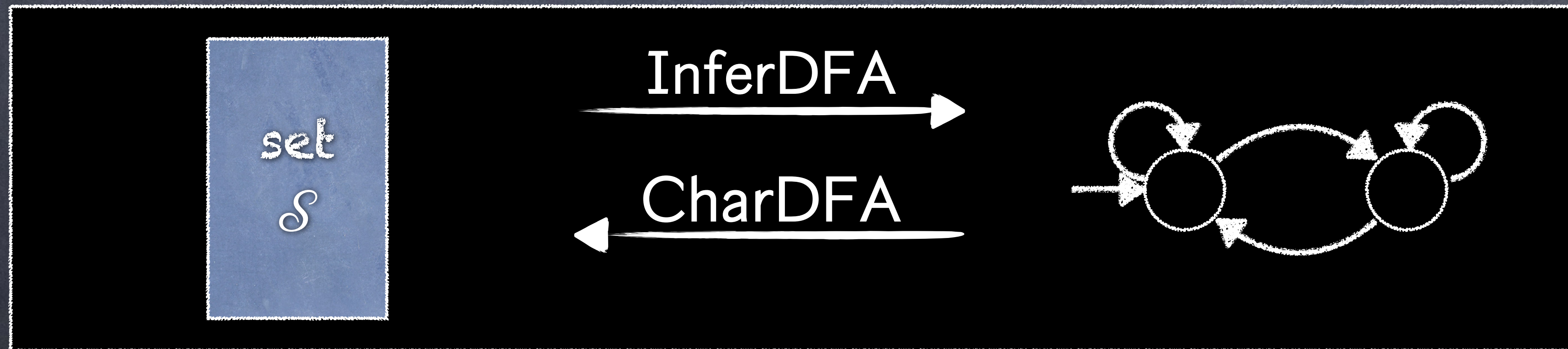
Identification in the Limit Using Polynomial Time and Data



Identification in the Limit Using Polynomial Time and Data



Identification in the Limit for DFAs

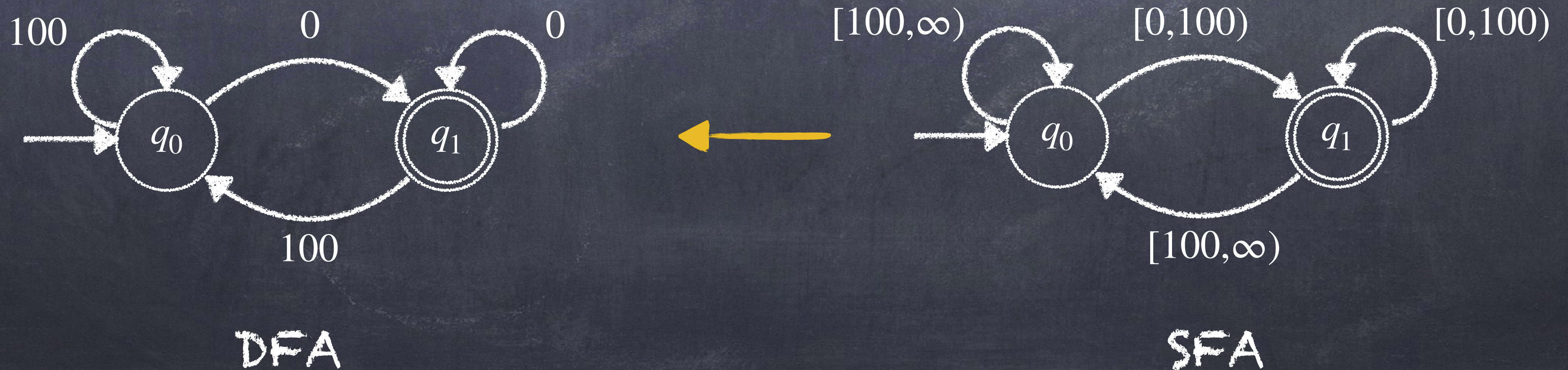


Concrete Sample set

DFA

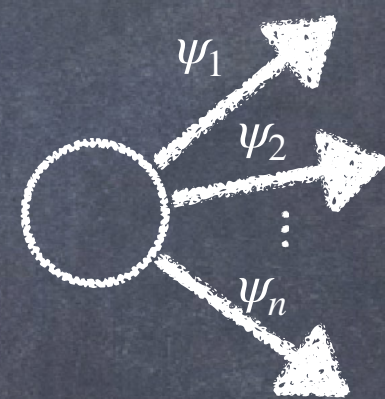
Identification in the Limit for SFAs - CharSFA

- Learning with respect to the concrete alphabet
- Creating a set of concrete words



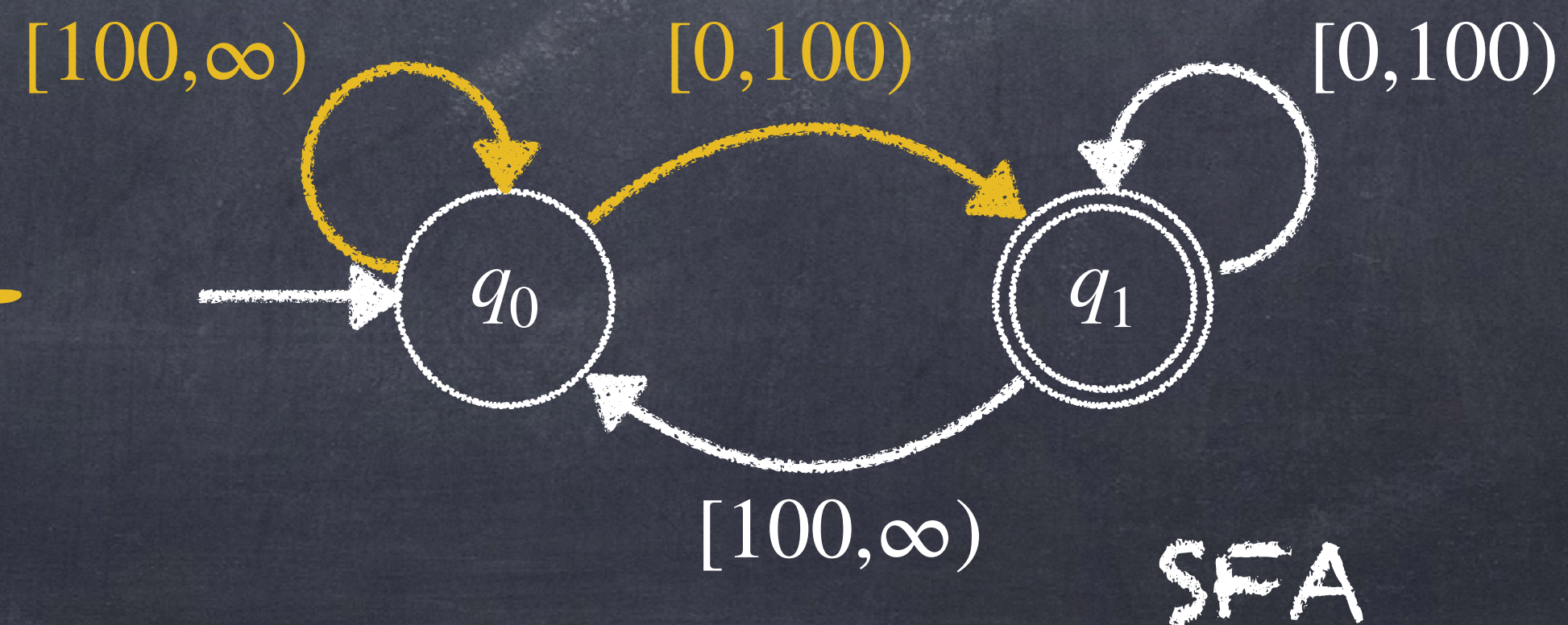
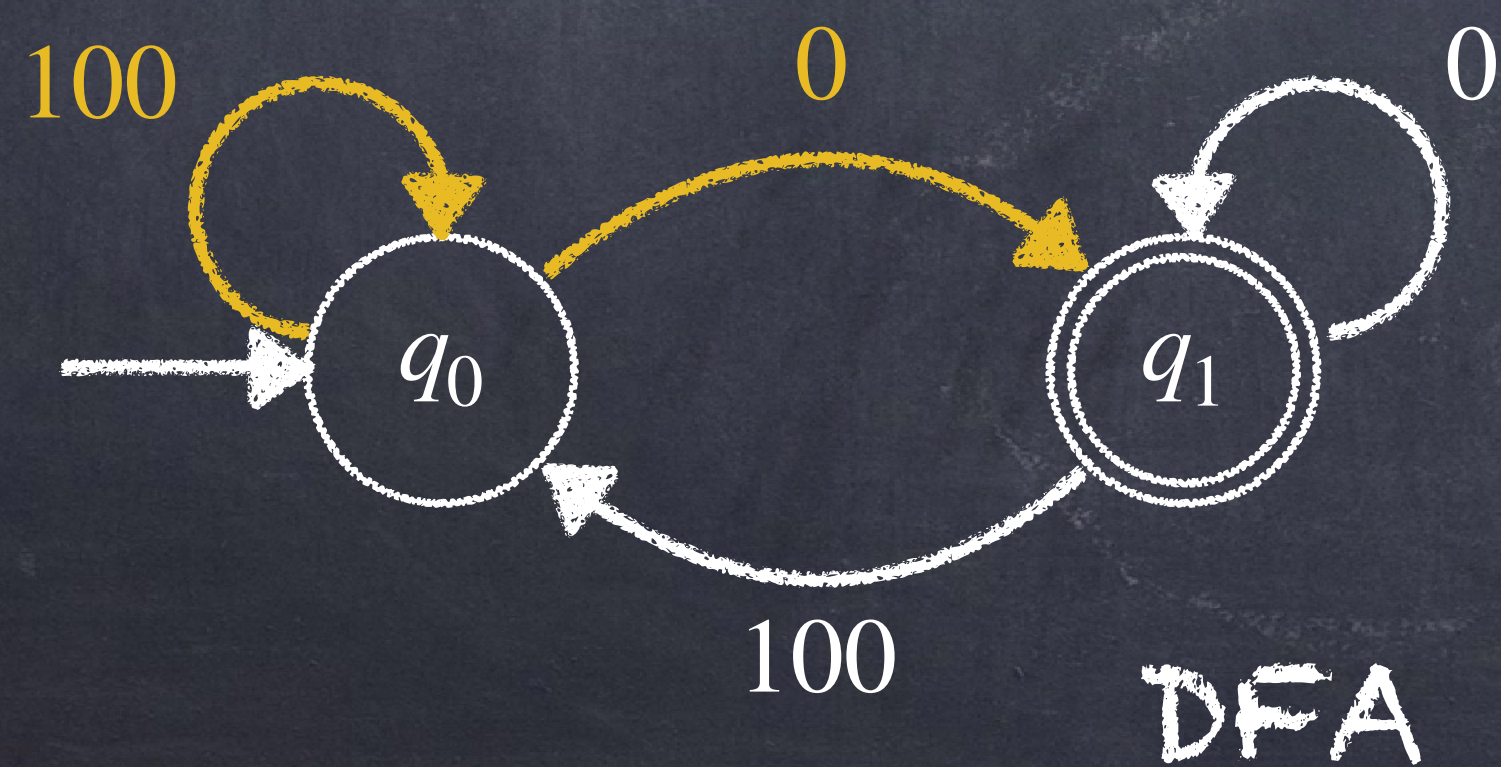
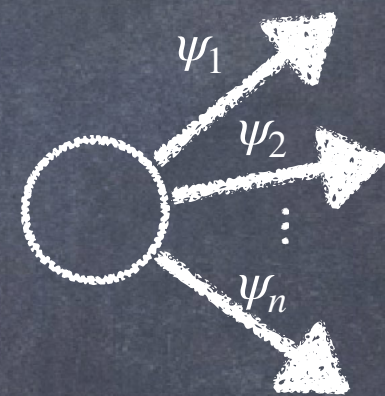
Identification in the Limit for SFAs - CharSFA

- Learning with respect to the concrete alphabet
- Creating a set of concrete words
- $\text{concretize}(\langle \psi_1, \dots, \psi_n \rangle) = \langle \Gamma_1, \dots, \Gamma_n \rangle$



Identification in the Limit for SFAs - CharSFA

- Learning with respect to the concrete alphabet
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- $\text{concretize}(\langle \psi_1, \dots, \psi_n \rangle) = \langle \Gamma_1, \dots, \Gamma_n \rangle$
- $\text{concretize}(\langle [0, 100), [100, \infty) \rangle) = \langle \{0\}, \{100\} \rangle$

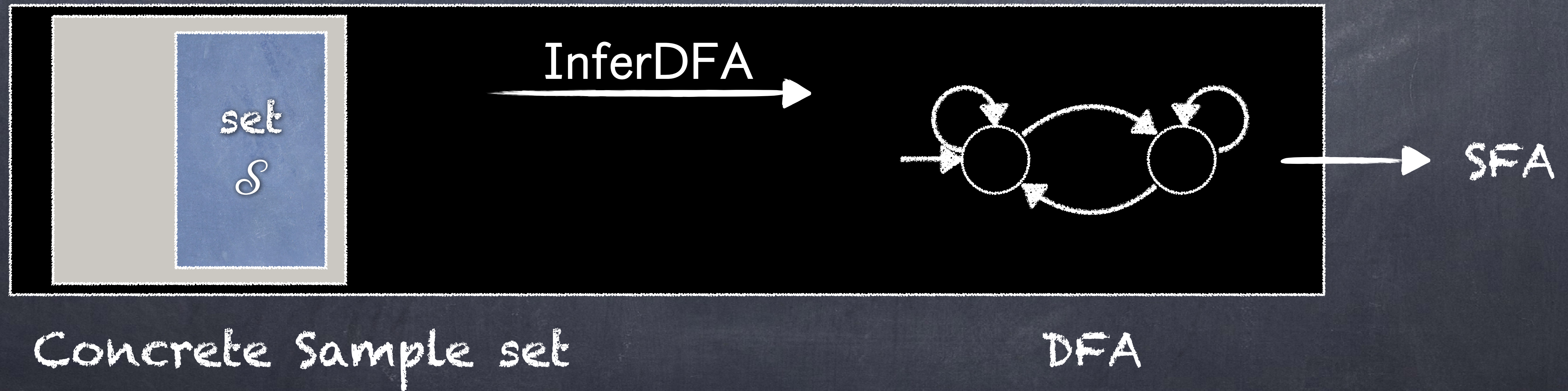


Identification in the Limit for SFAs - CharSFA

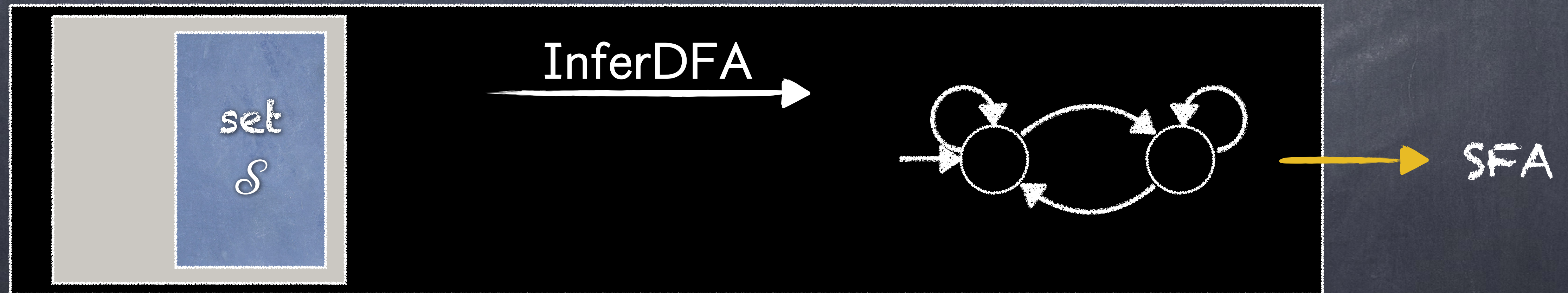
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Identification in the Limit for SFAs - InferSFA



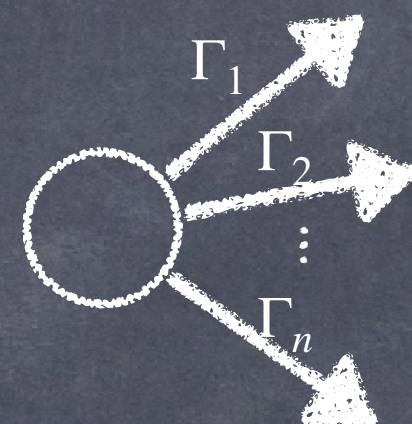
Identification in the Limit for SFAs - InferSFA

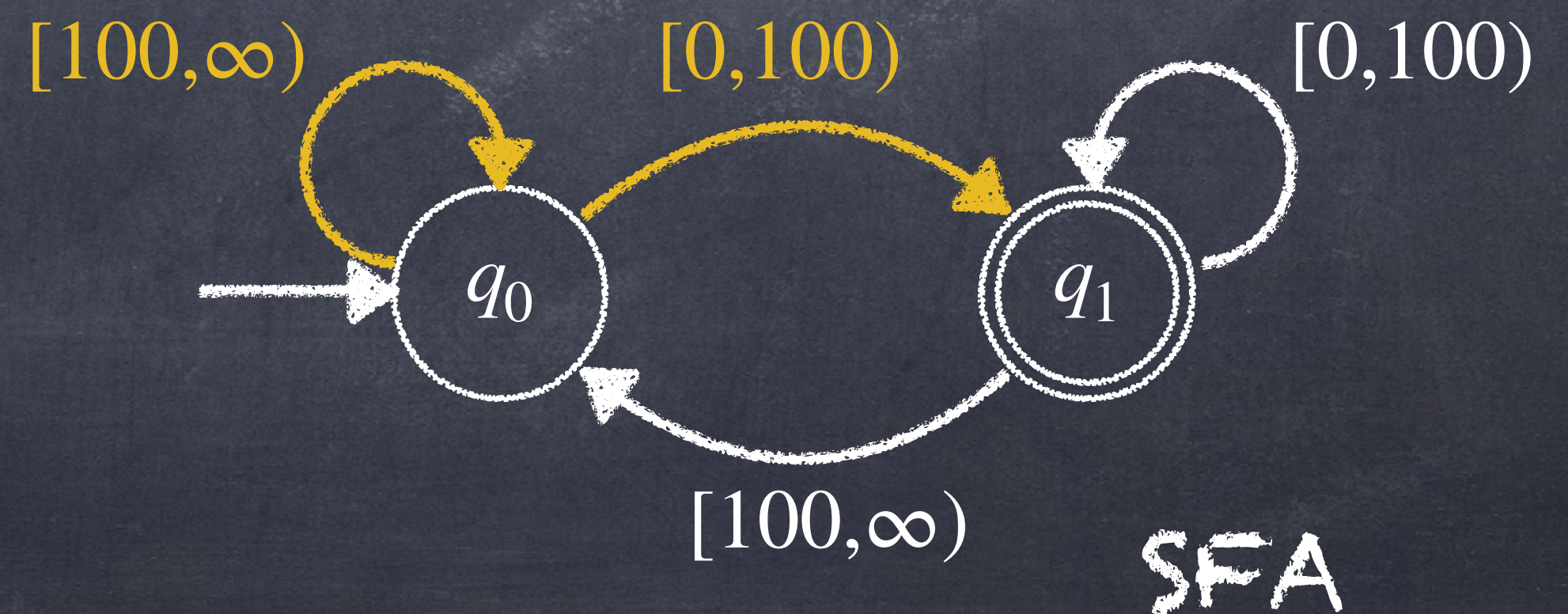
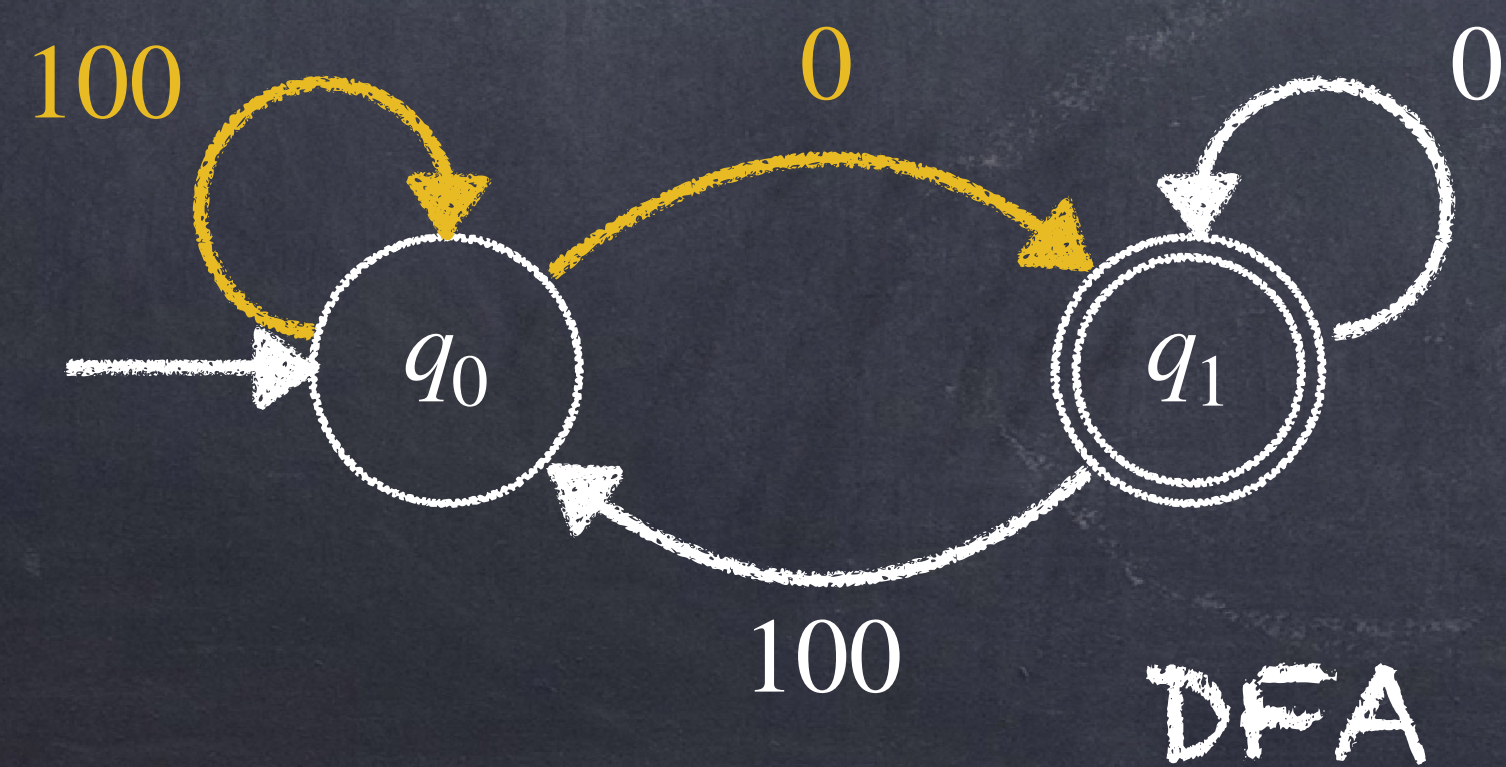


Concrete Sample set

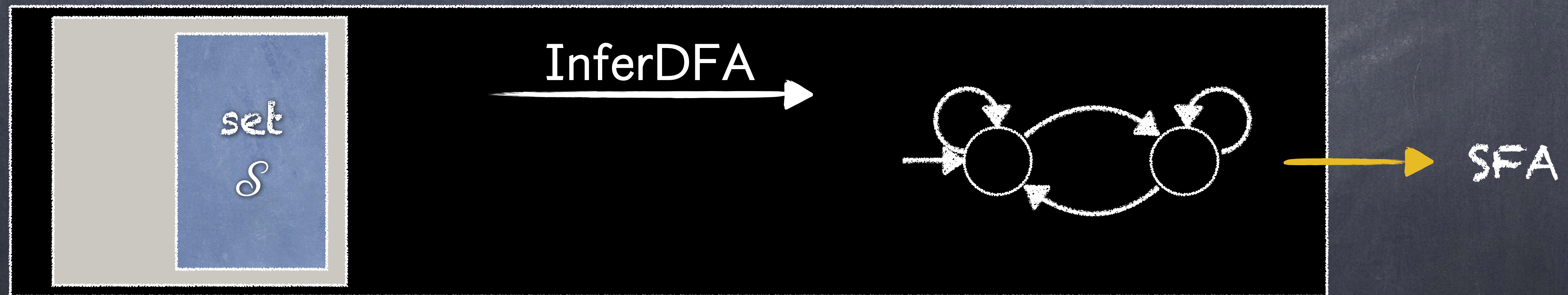
DFA **Generalize**

Identification in the Limit for SFAs - InferSFA

- $\text{generalize}(\langle \Gamma_1, \dots, \Gamma_n \rangle) = \langle \psi_1, \dots, \psi_n \rangle$ 
- $\text{generalize}(\langle \{0\}, \{100\} \rangle) = \langle [0, 100), [100, \infty) \rangle$



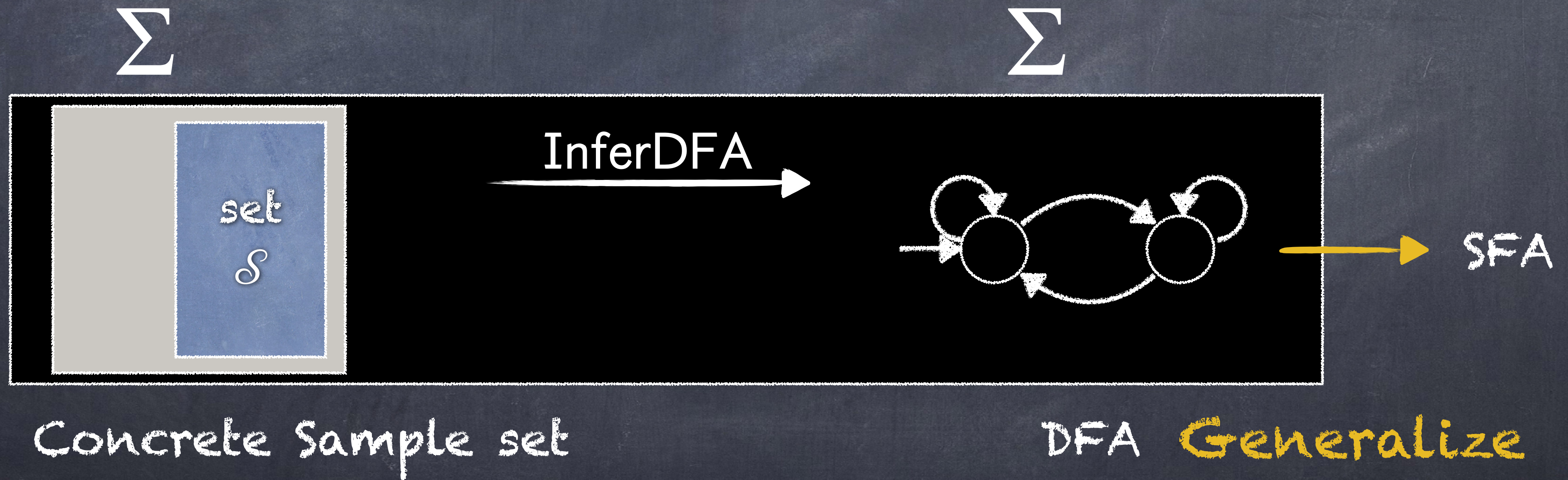
Identification in the Limit for SFAs - InferSFA



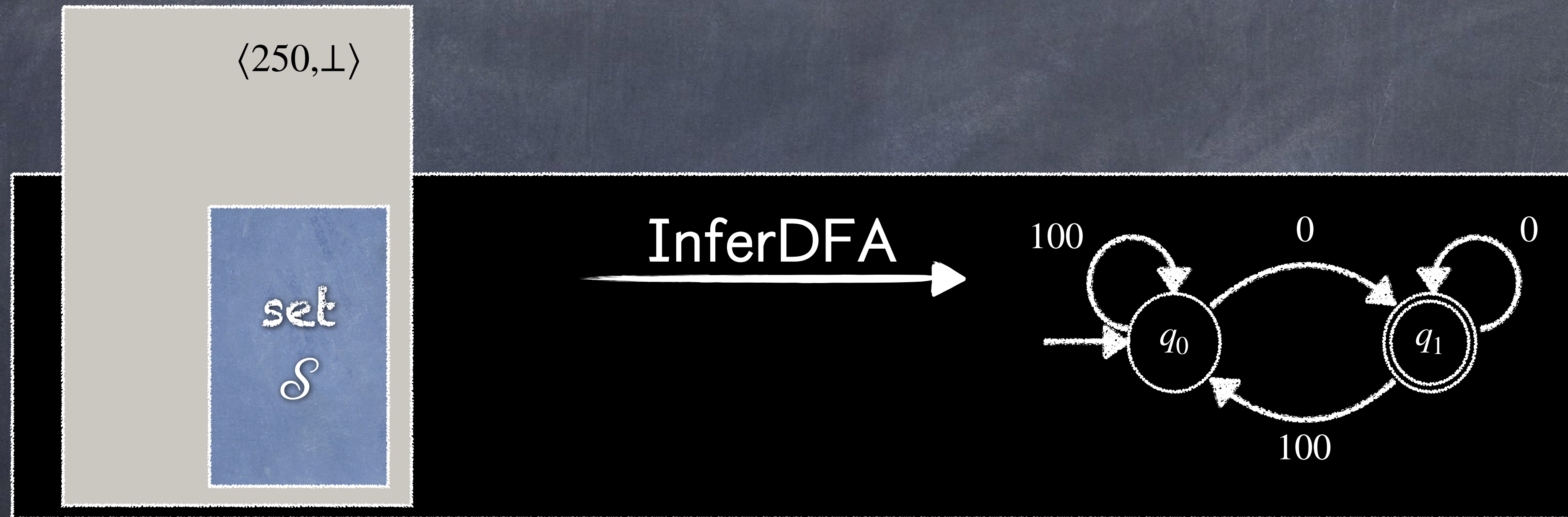
Concrete Sample set

DFA **Generalize**

Identification in the Limit for SFAs - InferSFA



Identification in the Limit for SFAs - InferSFA

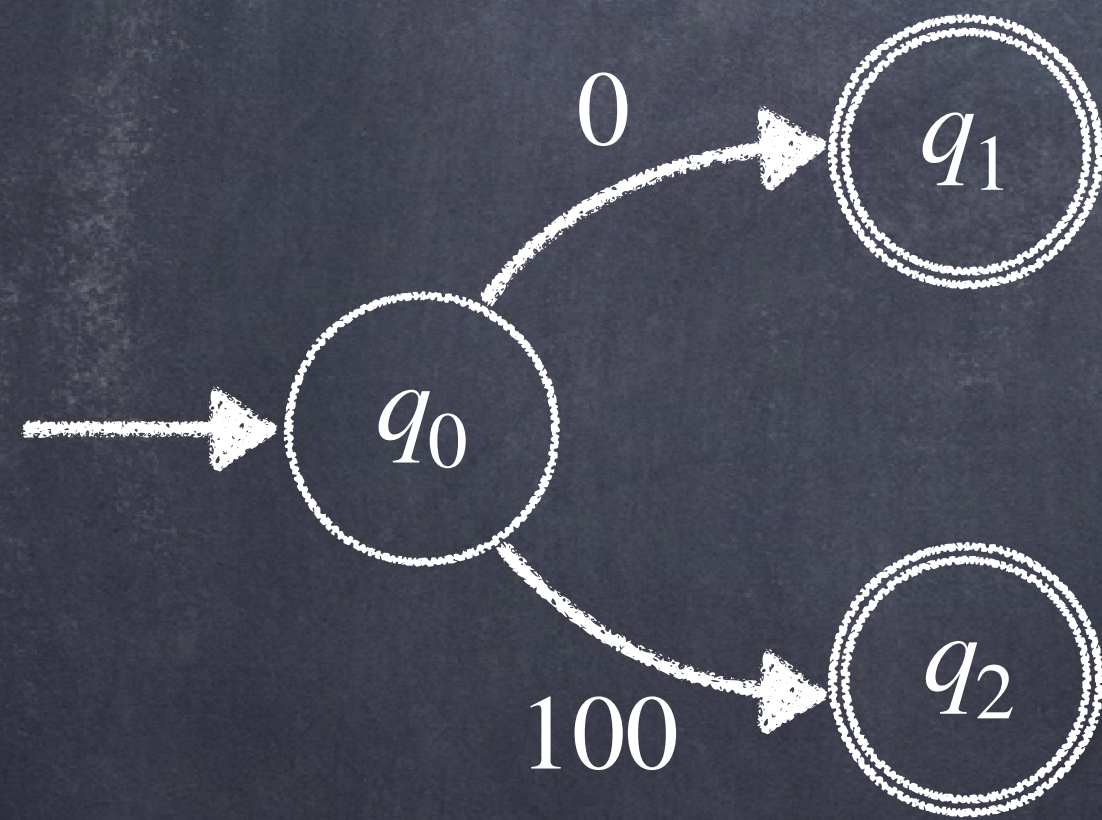


Concrete Sample set

DFA

Identification in the Limit for SFAs - InferSFA

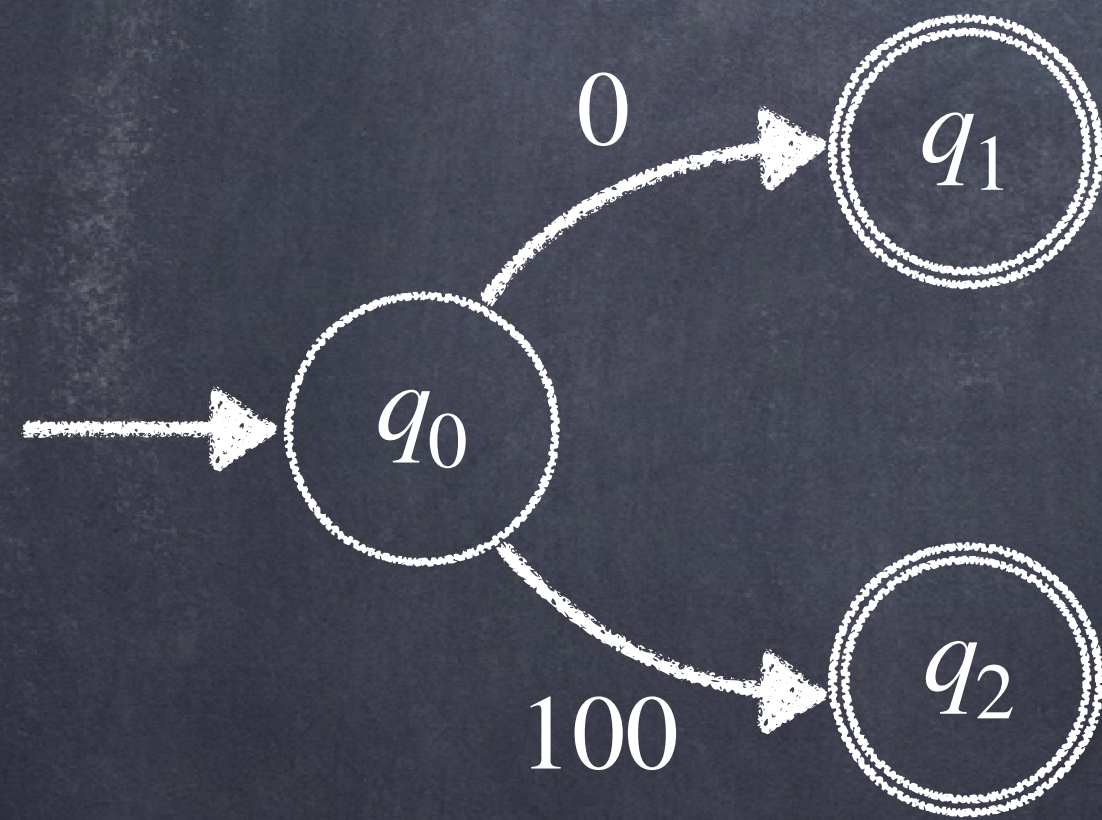
- Additional alphabet adds confusion



$\langle \epsilon, \perp \rangle, \langle 0, T \rangle, \langle 100, T \rangle$

Identification in the Limit for SFAs - InferSFA

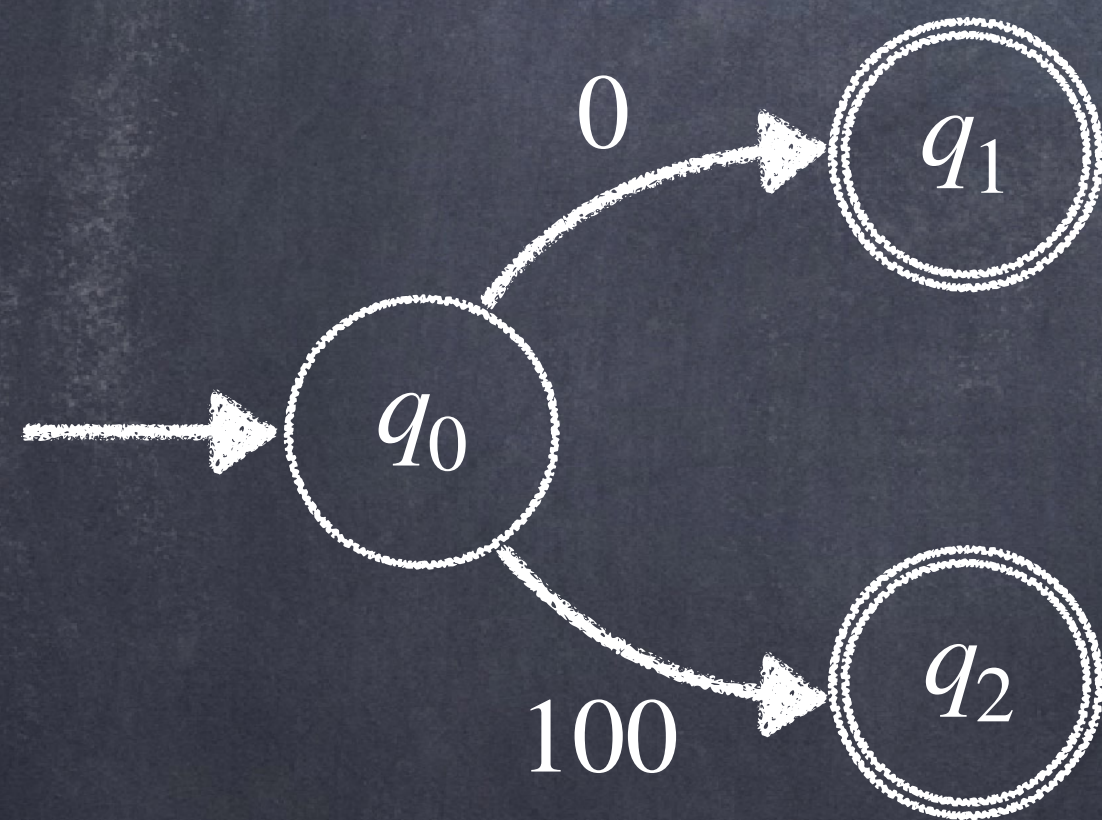
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 $\langle 0 \cdot 0, T \rangle, \langle 100 \cdot 0, \perp \rangle$

Identification in the Limit for SFAs - InferenceSFA

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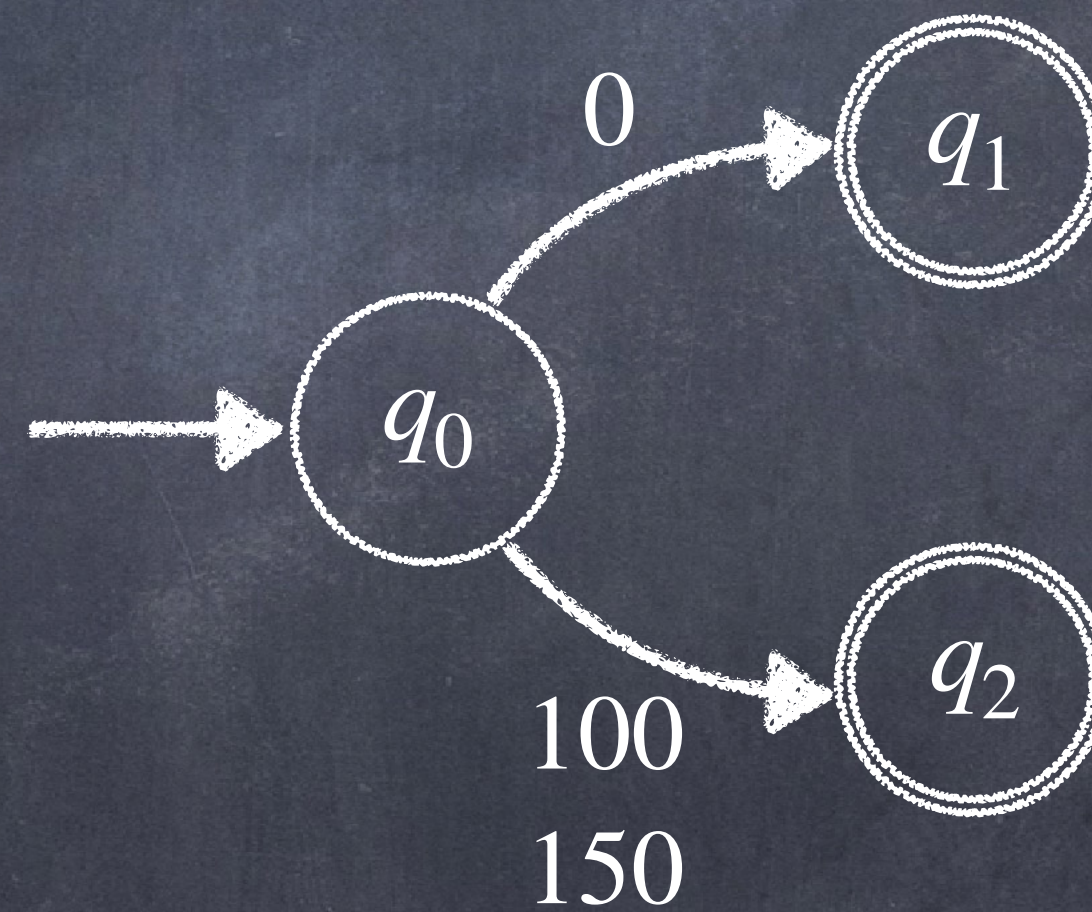
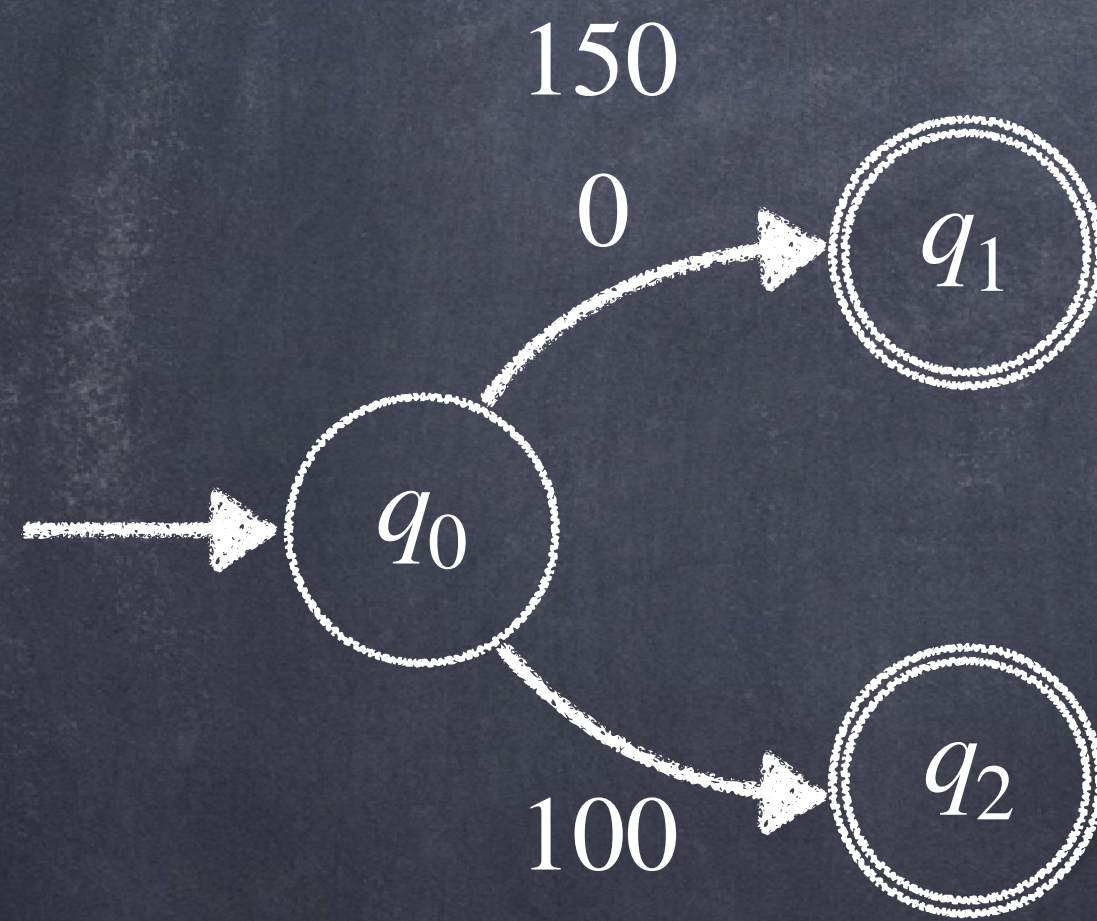
$\langle \epsilon, \perp \rangle, \langle 0, T \rangle, \langle 100, T \rangle$

$\langle 0 \cdot 0, T \rangle, \langle 100 \cdot 0, \perp \rangle$

$\langle 150, T \rangle$

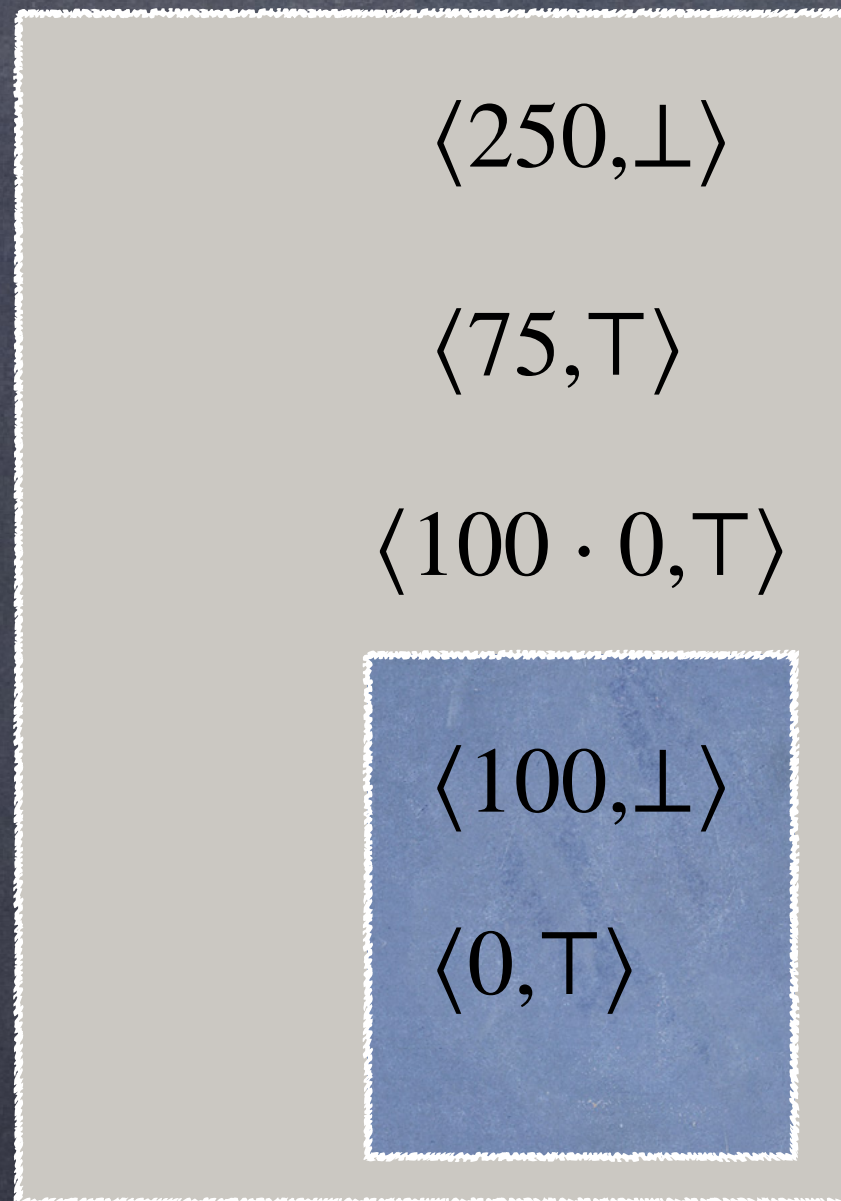
Identification in the Limit for SFAs - InferSFA

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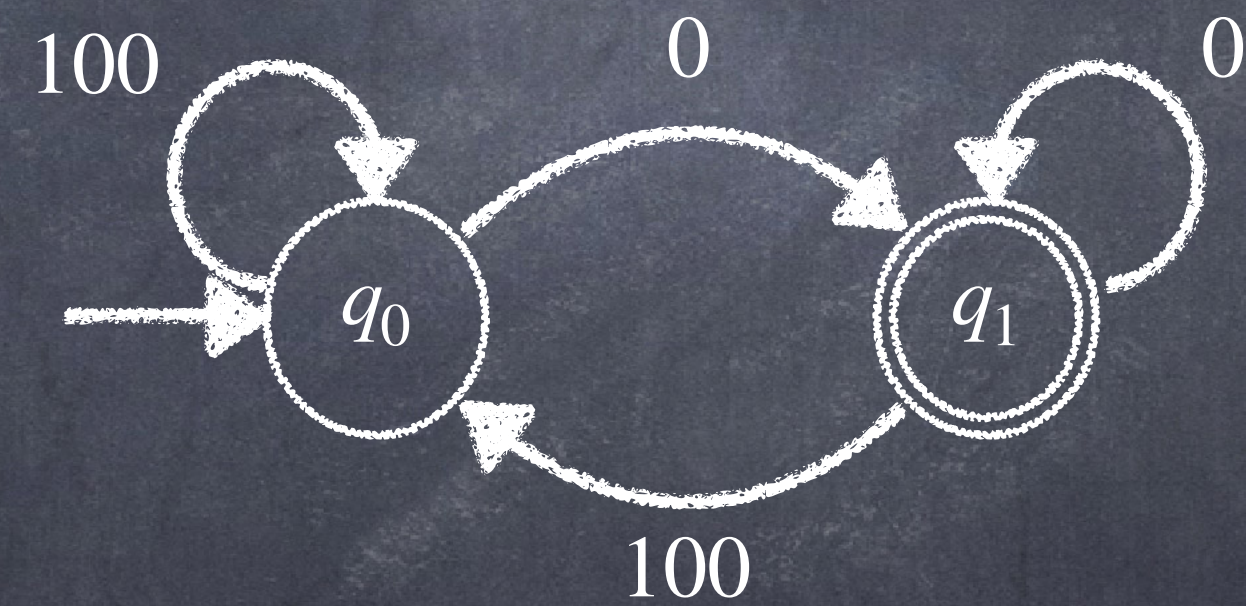
$\langle \epsilon, \perp \rangle, \langle 0, T \rangle, \langle 100, T \rangle$
 $\langle 0 \cdot 0, T \rangle, \langle 100 \cdot 0, \perp \rangle$
 $\langle 150, T \rangle$

Identification in the Limit for SFAs - InfeRSFA



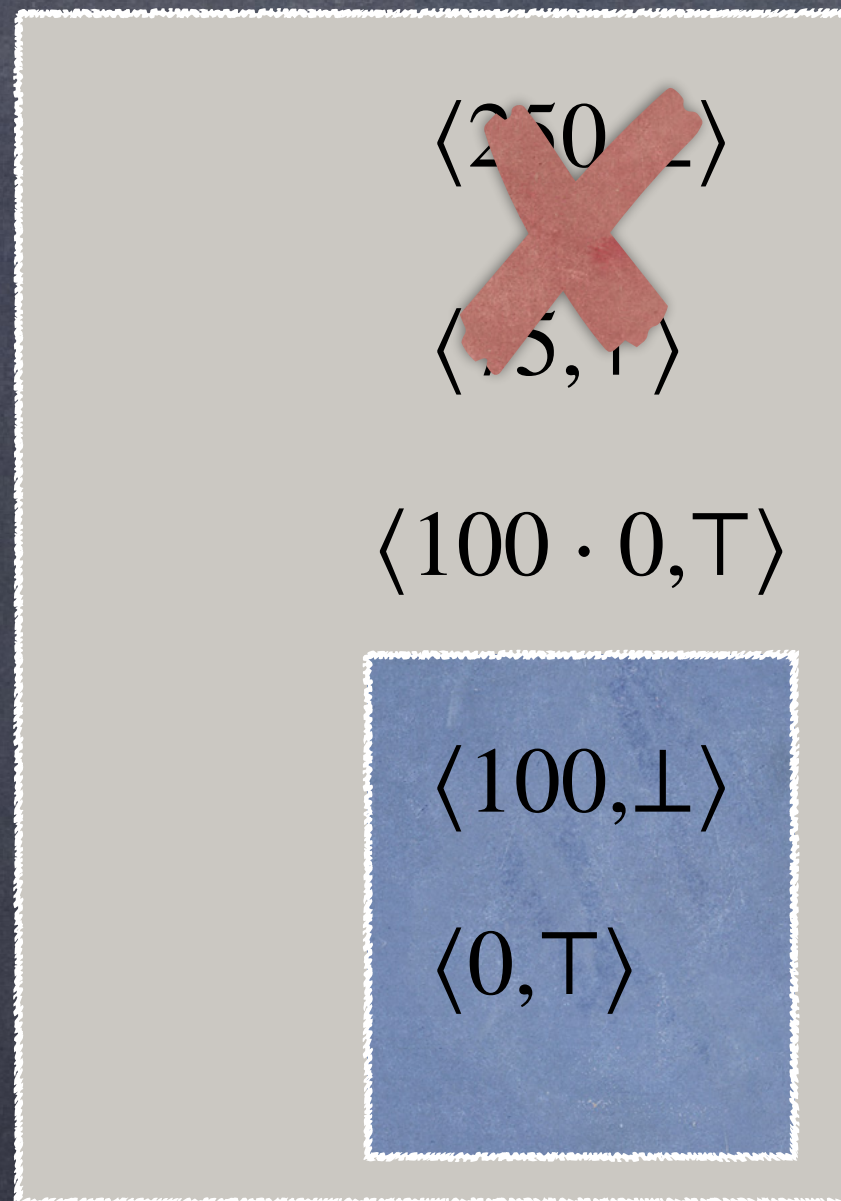
Decontaminate

Concrete Sample set

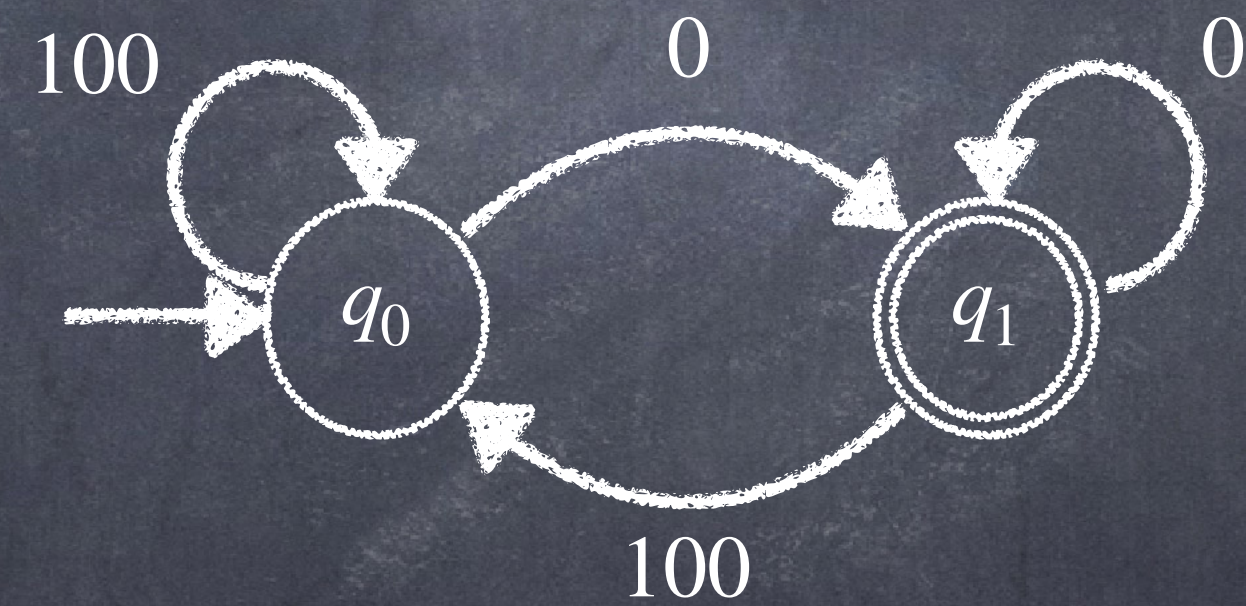


DFA

Identification in the Limit for SFAs - InfeRSFA



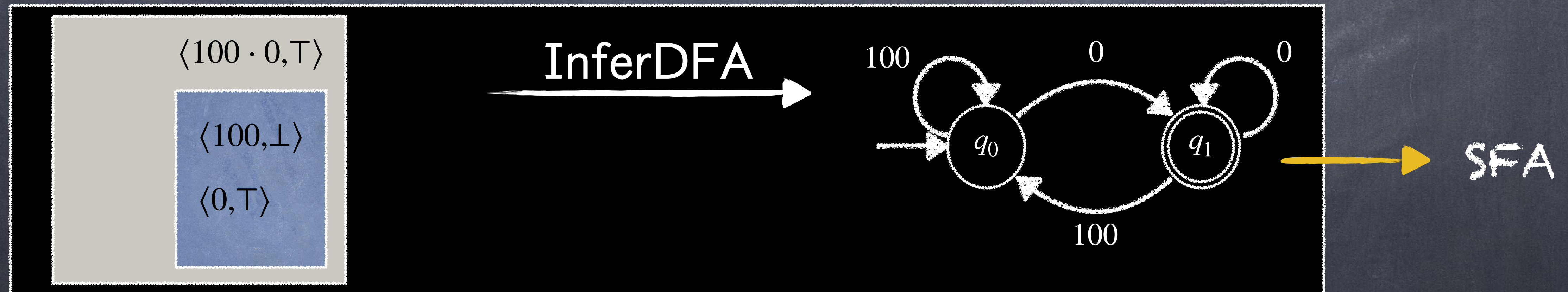
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Concrete Sample set

DFA

Identification in the Limit for SFAs - InferSFA

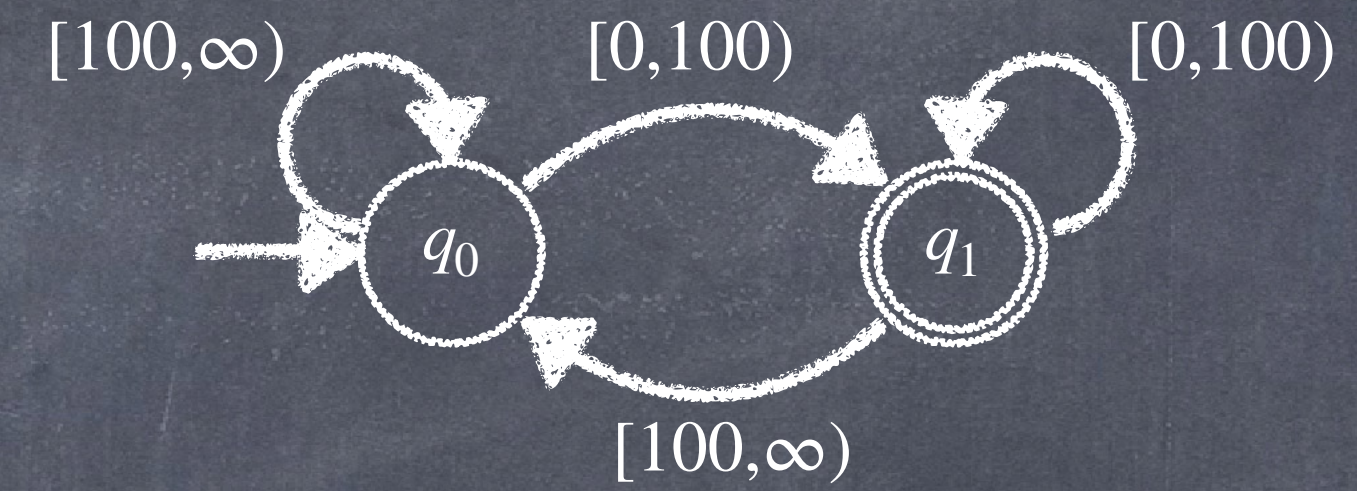


Concrete Sample set

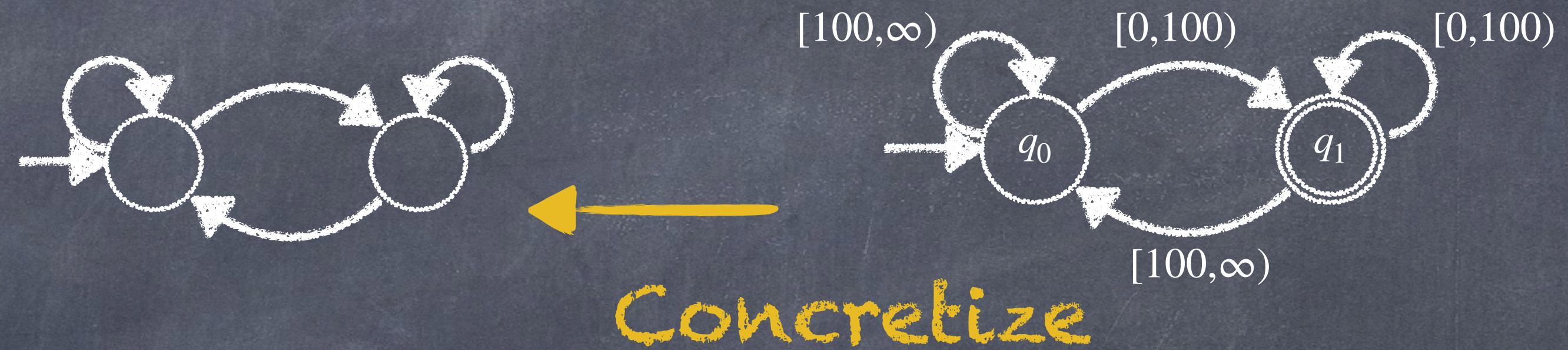
DFA **Generalize**

The Whole Process

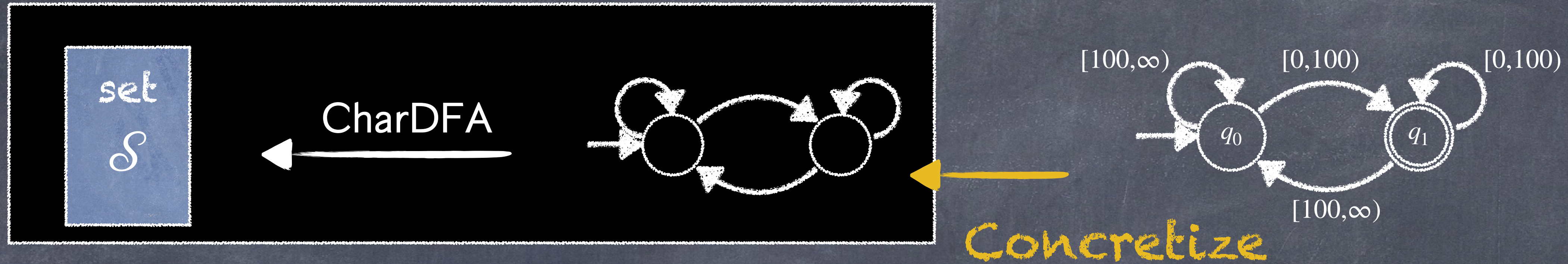
The Whole Process



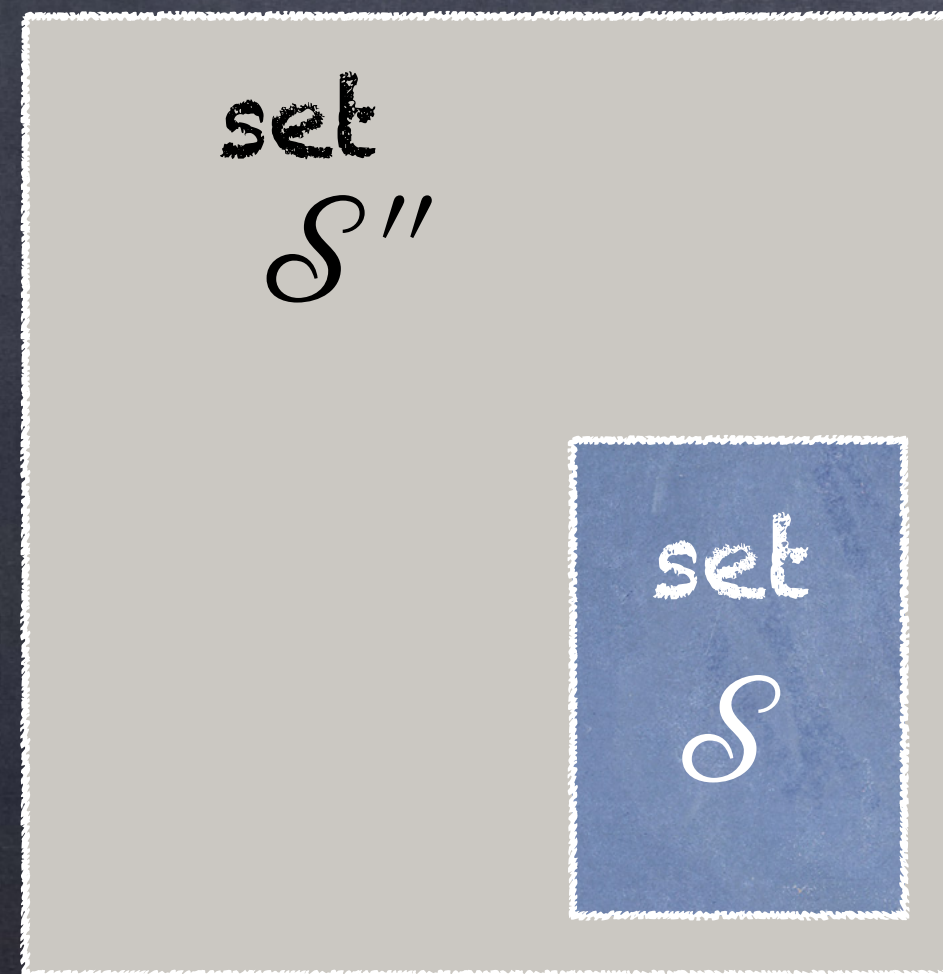
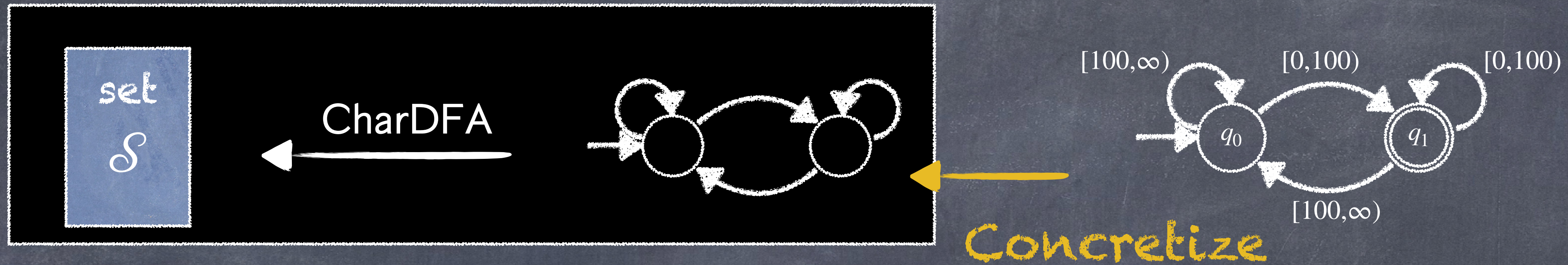
The Whole Process



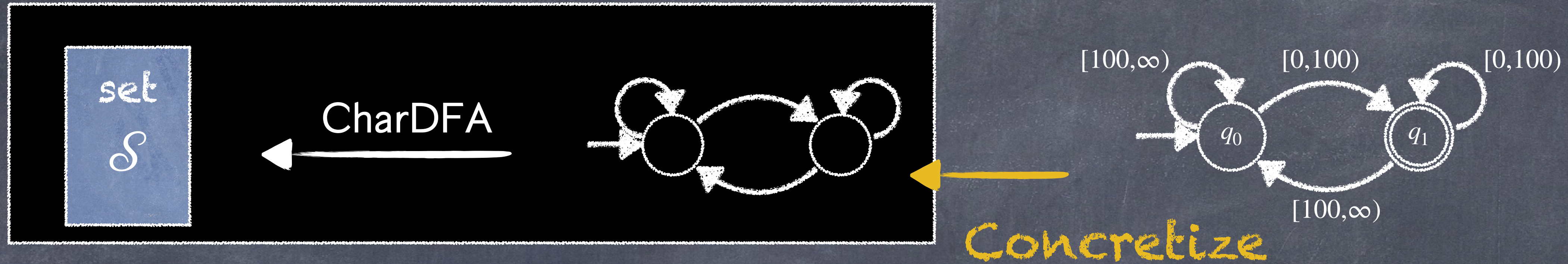
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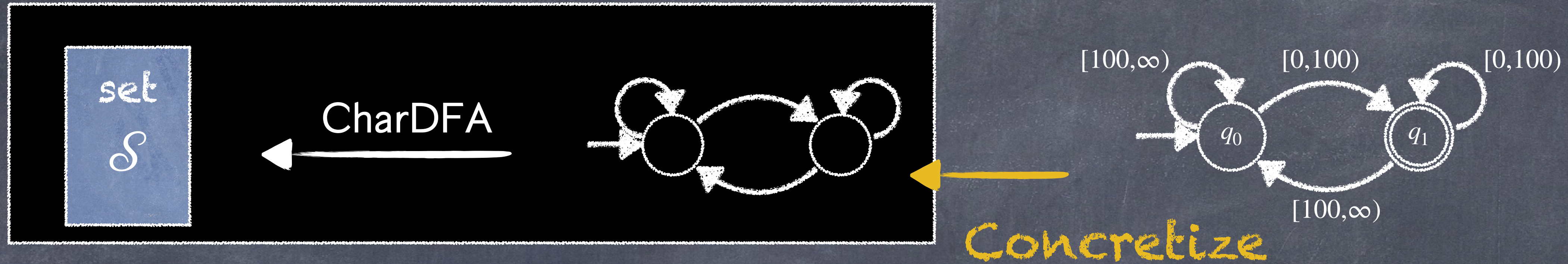
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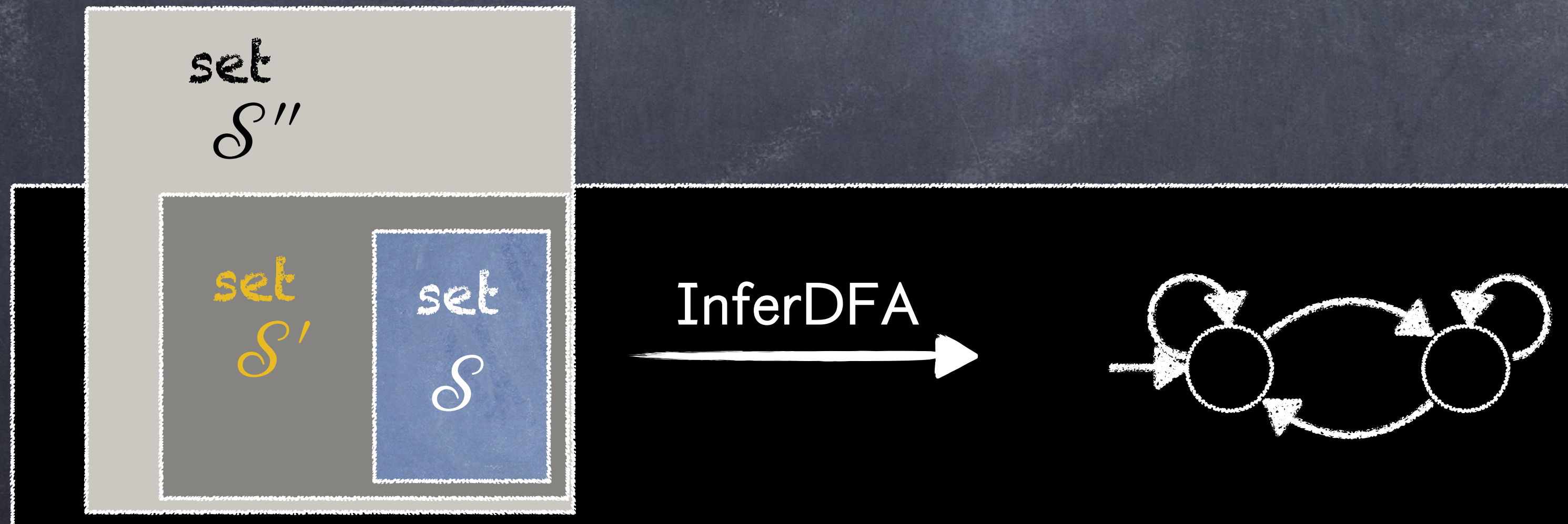
Decontaminate



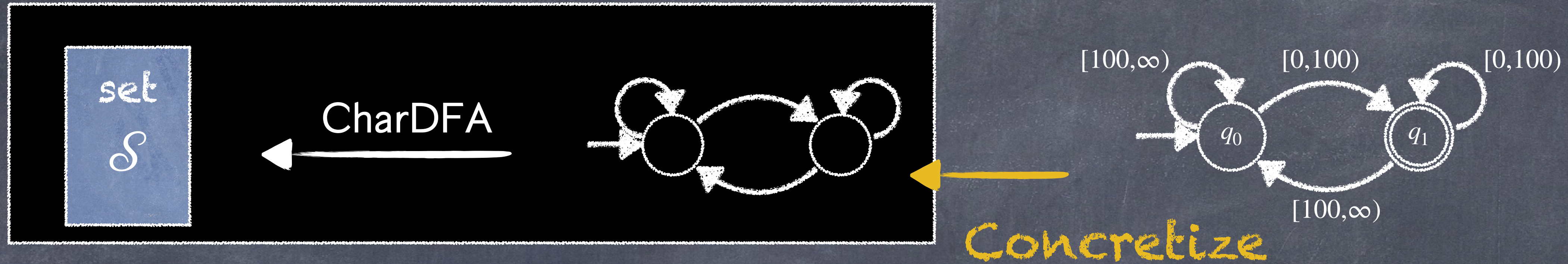
The Whole Process



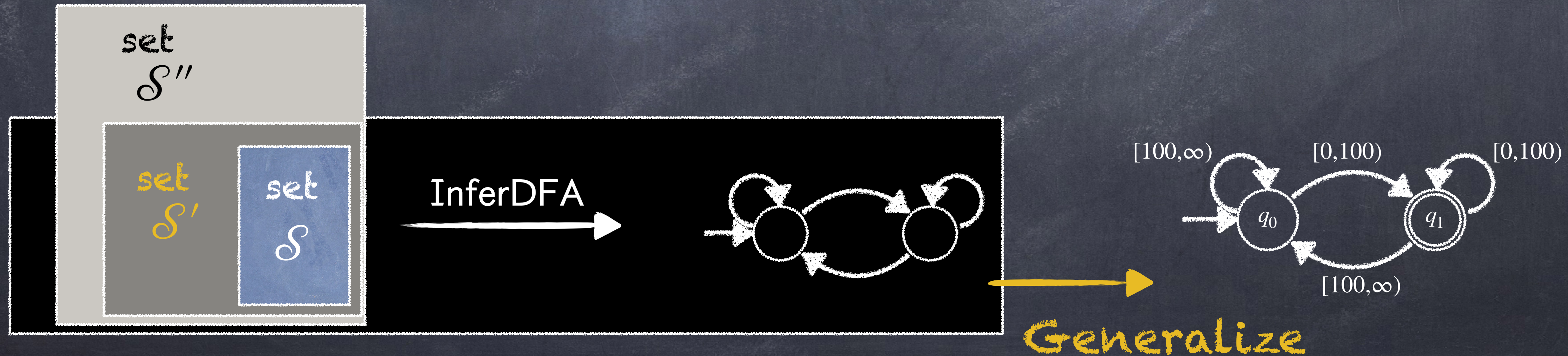
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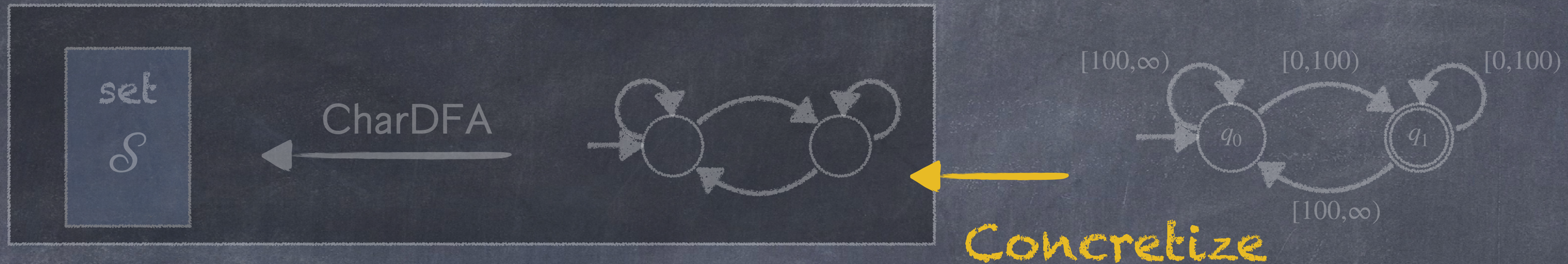
The Whole Process



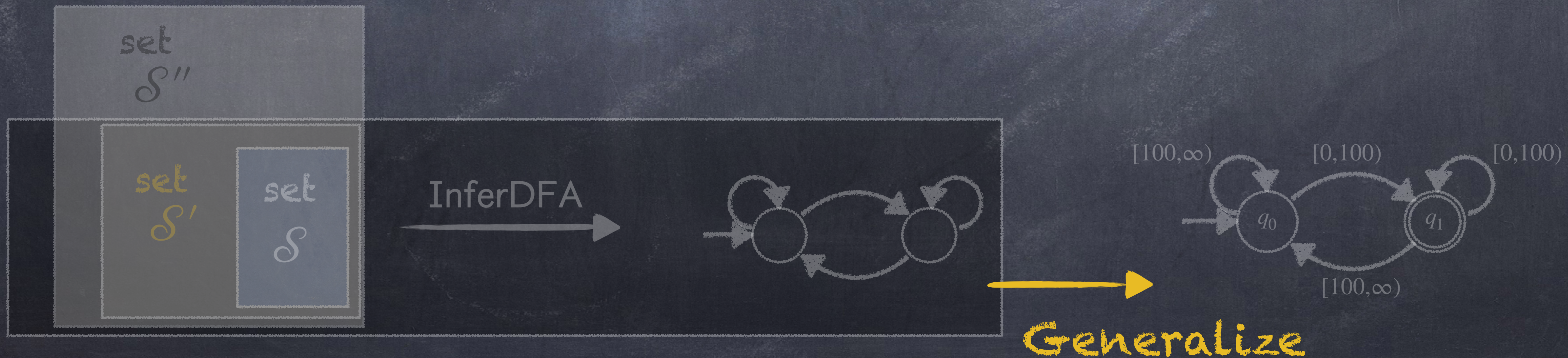
Decontaminate



Sufficient Condition



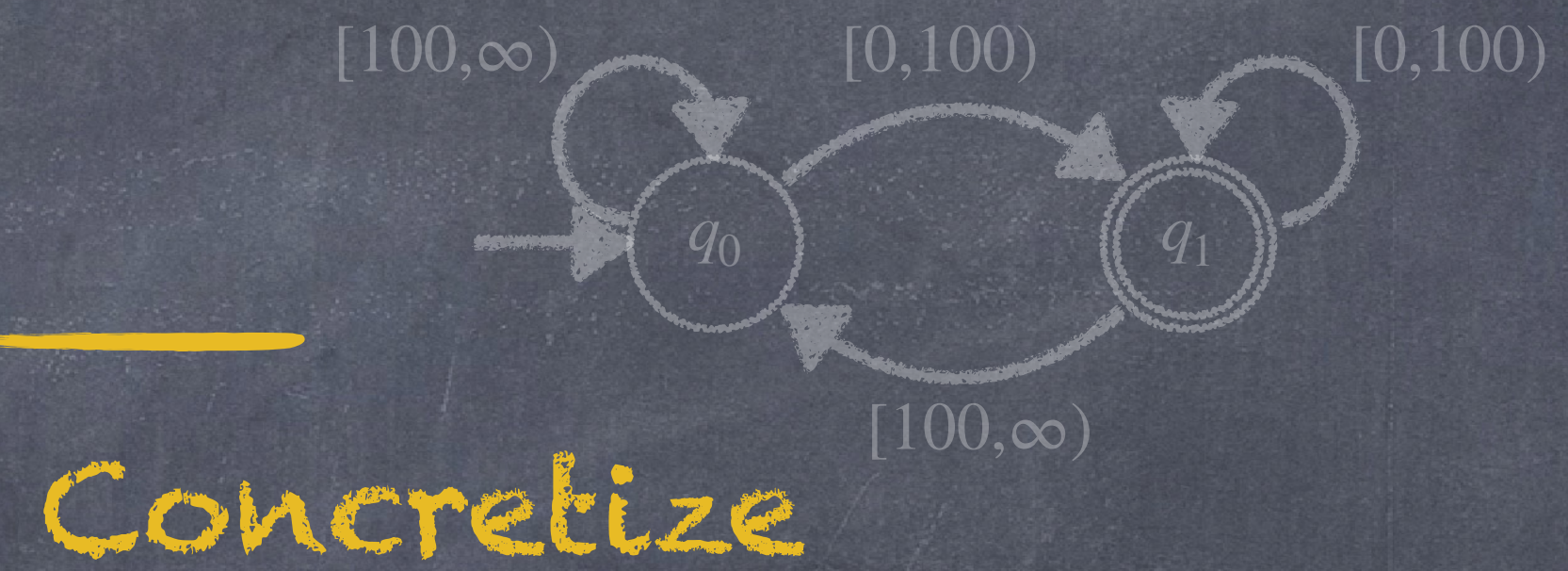
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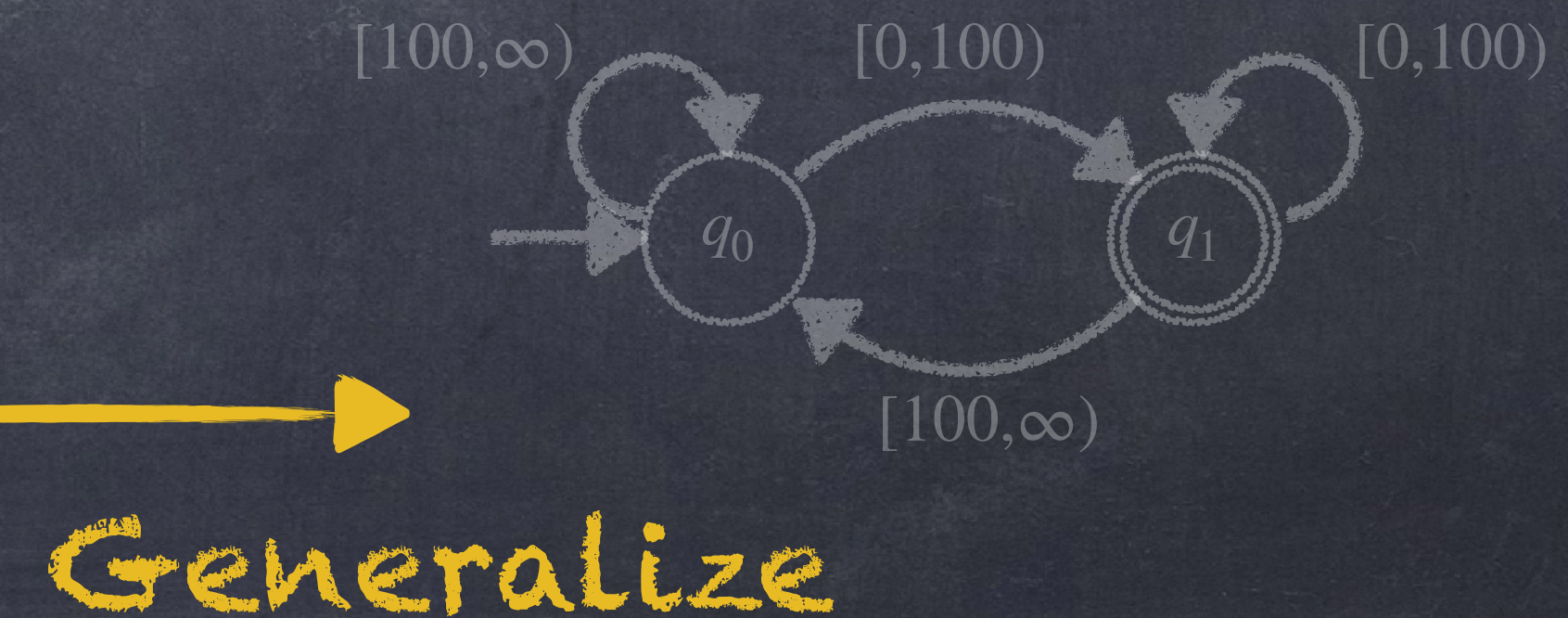
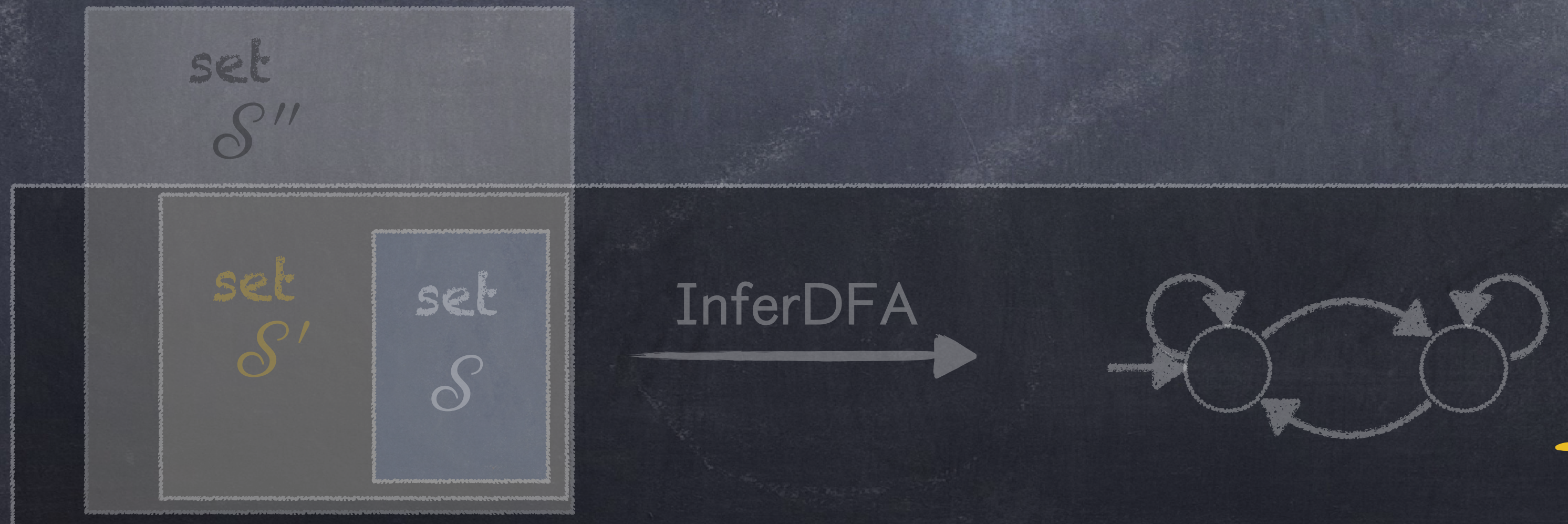


Sufficient Condition

Monotonic algebras



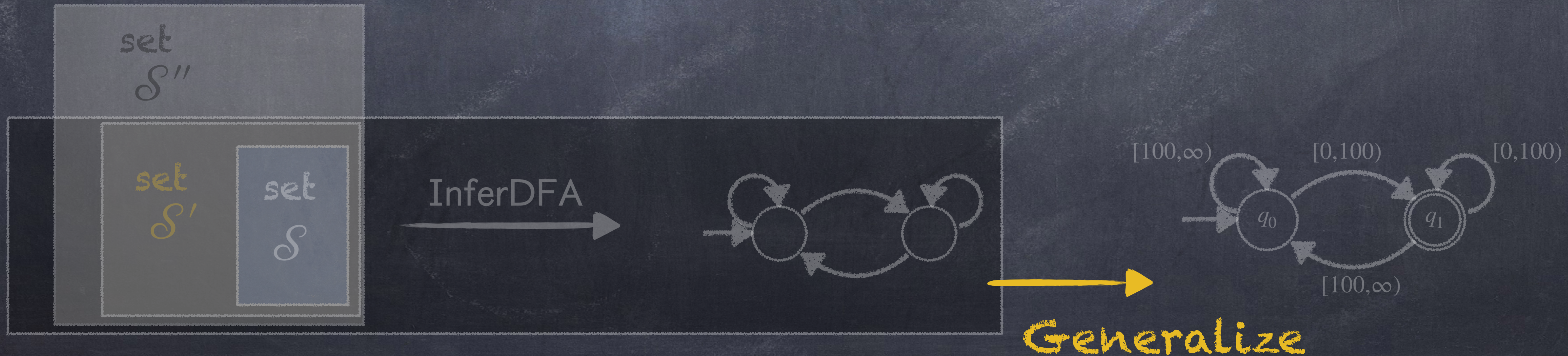
Decontaminate



Necessary Condition



Decontaminate



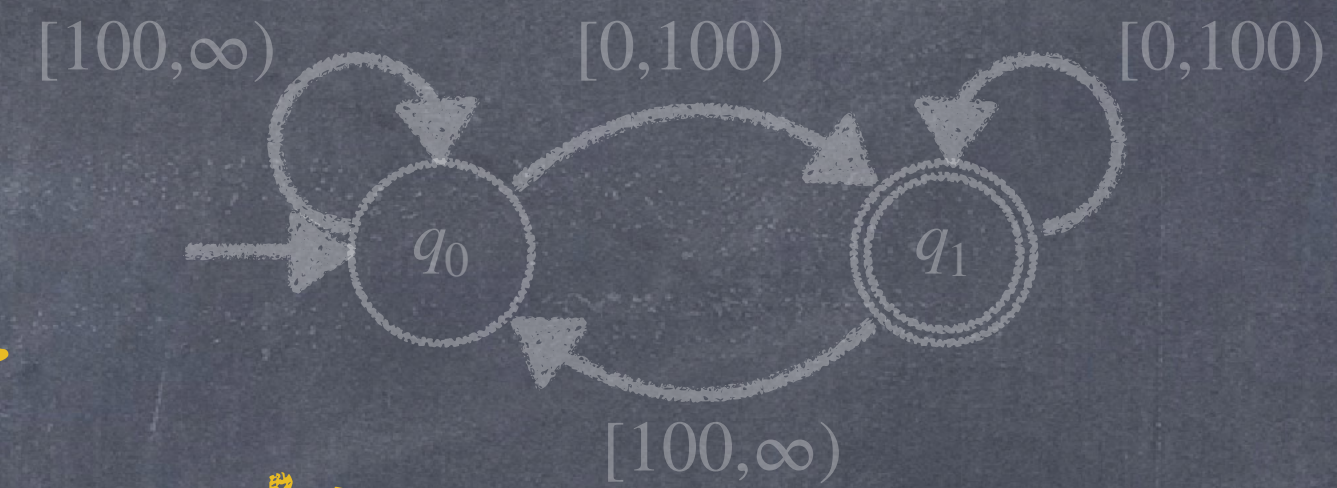


Necessary Condition

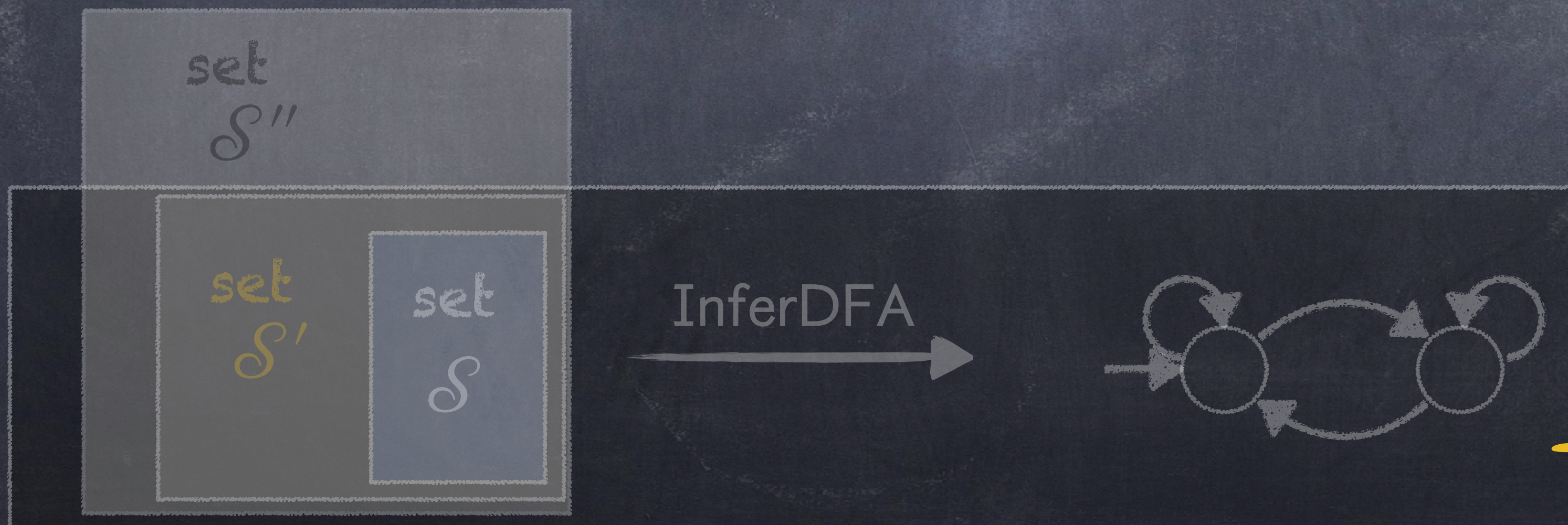
Propositional Algebra



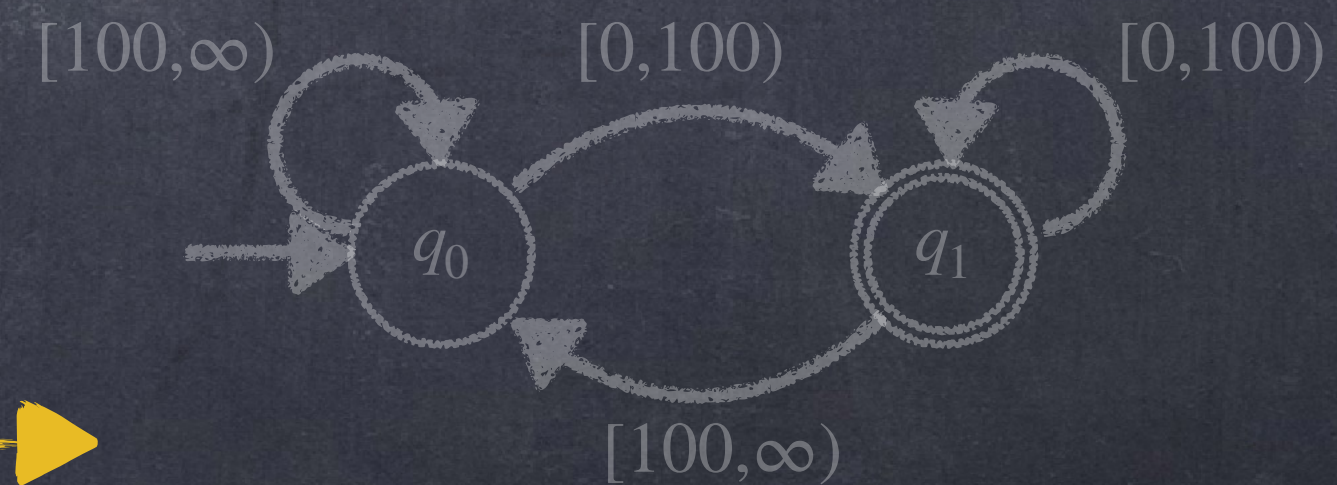
Concretize



Decontaminate



Generalize



Summary

- Active Learning
 - Necessary condition
 - SFAs over the propositional algebra are not polynomially learnable



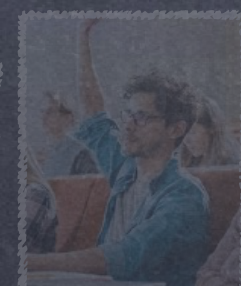
Summary

- Active Learning

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- Necessary condition & sufficient condition for learning SFAs



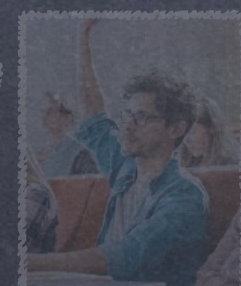
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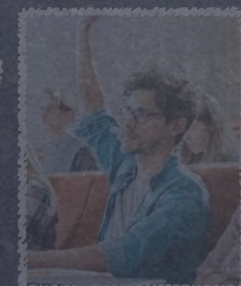
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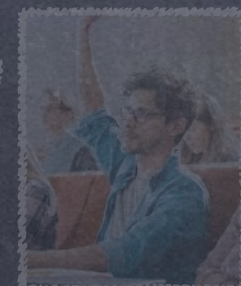
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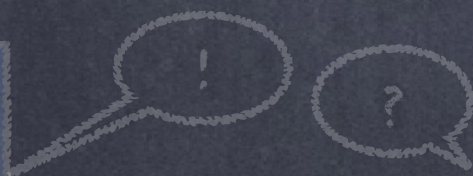


- Necessary condition & sufficient condition for learning SFAs
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- Learning scheme for the paradigm of identification in the limit of SFAs

THANK YOU!

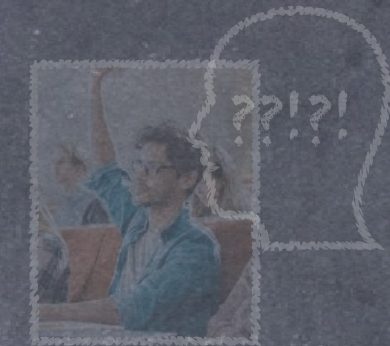
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Questions?