

# Learning System Abstractions for Human Operators

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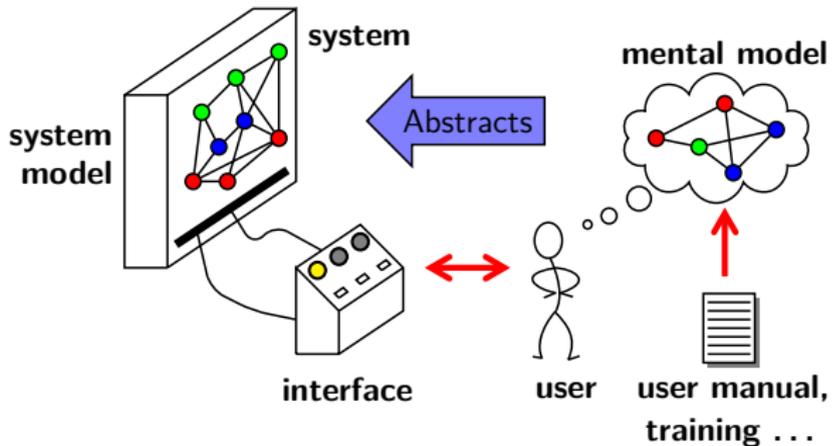
# CAVEAT

This is NOT  
Learning

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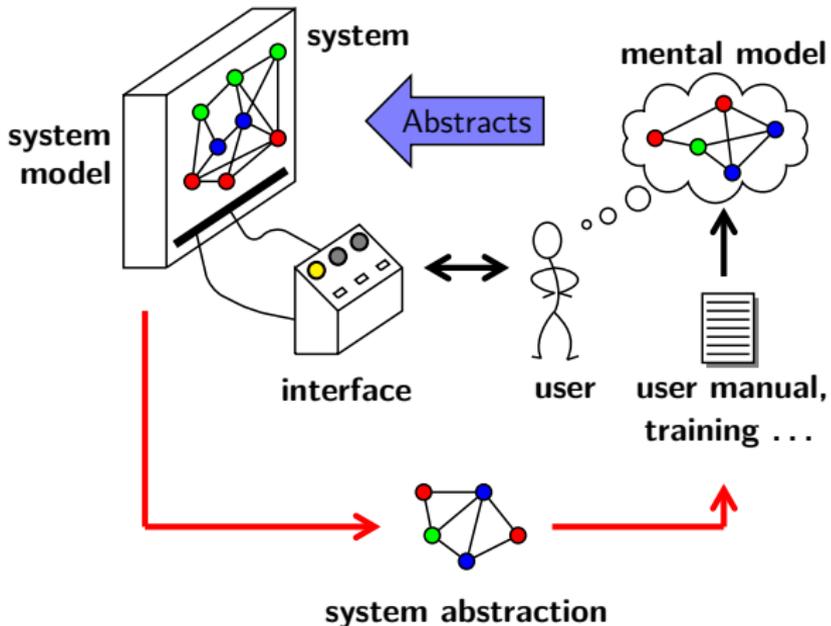
This is NOT (your usual kind of)  
Learning (either)

# Human-Machine Interaction



- What is a good system abstraction?

# Human-Machine Interaction



- How can such an abstraction be automatically generated?

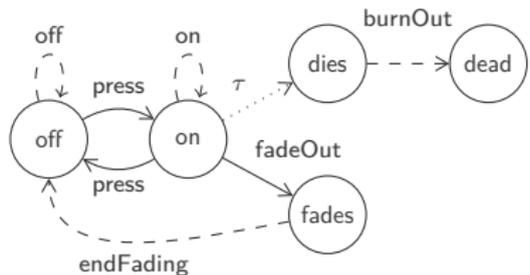
# Outline

- 1 Modelling and Interaction Analysis
- 2 Learning-Based System Abstraction's Generation
- 3 Prototype and Experiments
- 4 Conclusions

# Modelling



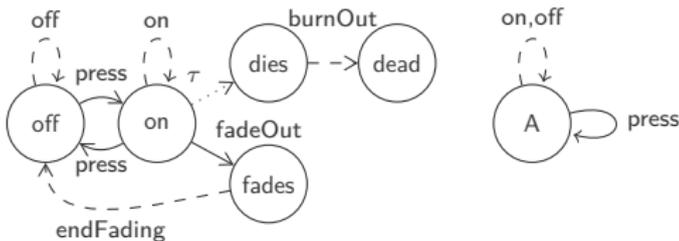
- System modelled as an **HMI-LTS**
- (Finite) LTS
- **Commands, observations** and  $\tau$



- **Full-control** = good abstraction
- During interaction:
  - same set of commands
  - user expects all possible observations

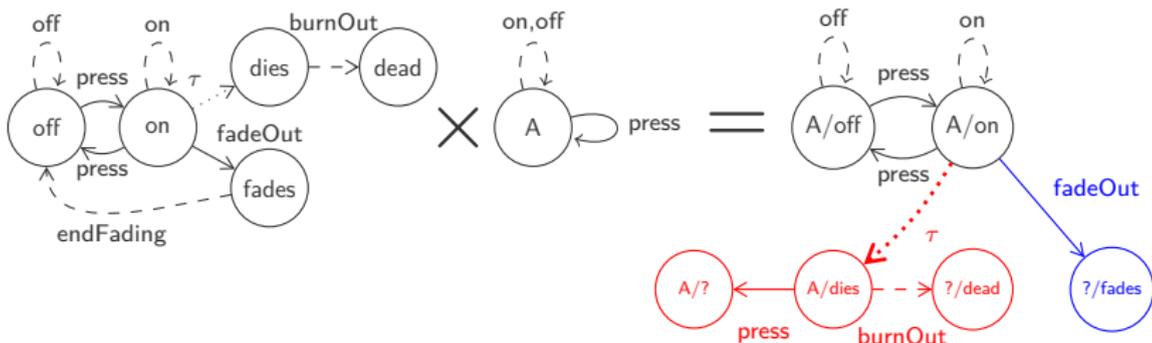
# Interaction Analysis

- Interaction between a user and a system through two models:
  - **System model** models behaviour of the system
  - **Mental model** is an abstraction of the system model capturing the knowledge of the operator (conceptual model)
- The **interaction** is captured by the parallel execution of the two models



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# Full-control property

- **Full-control property** captures good system abstraction
- During the **interaction** between user and system:
  - The user should know exactly the available commands ...
  - ... and at least all the possible observations
- Given a **system**  $\mathcal{M}_M = \langle S_M, s_{0_M}, \mathcal{L}^c, \mathcal{L}^o, \rightarrow_M \rangle$  and an **abstraction** for it  $\mathcal{M}_U = \langle S_U, s_{0_U}, \mathcal{L}^c, \mathcal{L}^o, \rightarrow_U \rangle$ :

$\mathcal{M}_U$  fc  $\mathcal{M}_M$  iff :

$\forall \sigma \in \mathcal{L}^{co*}$  such that  $s_{0_M} \xrightarrow{\sigma} s_M$  and  $s_{0_U} \xrightarrow{\sigma} s_U$  :

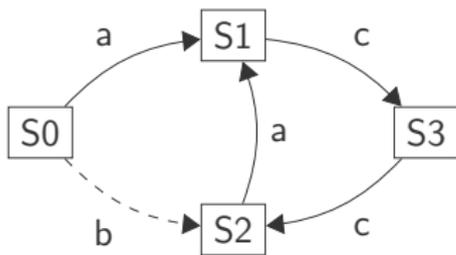
$$A^c(s_M) = A^c(s_U) \quad \wedge \quad A^o(s_M) \subseteq A^o(s_U)$$

# Generation Problem

- **Goal:** Given the model of a system, **automatically** generate a **minimal full-control** system abstraction
- **Motivation:**
  - Extract the minimal behaviour of the system, so that it can be controlled **without surprise**
  - Help to build **artifacts**: manuals, procedures, trainings, ...
  - If such abstraction does not exist, provide feedback to help **redesigning** the system
- Two developed algorithms : reduction-based (similarity relation) and learning-based ( $L^*$  and **3DFA**)

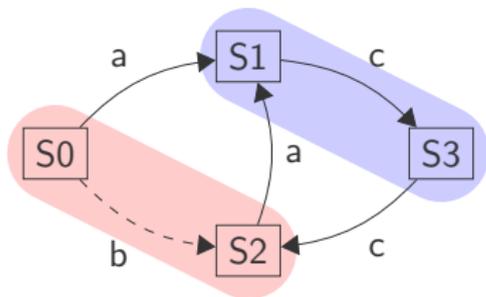
# Reduction-Based Approach

- Method based on a variant of the **Paige-Tarjan** reduction algorithm which will partition the system by separating states which exhibit different behaviour, based on a **similarity relation**



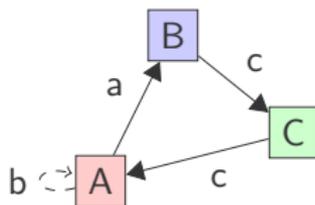
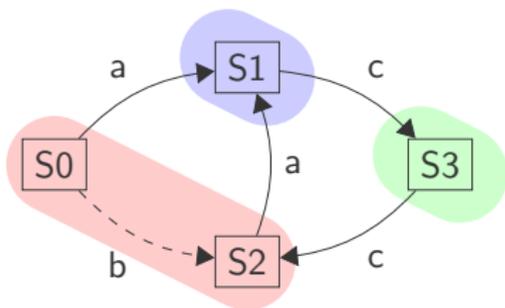
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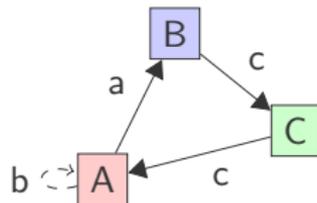
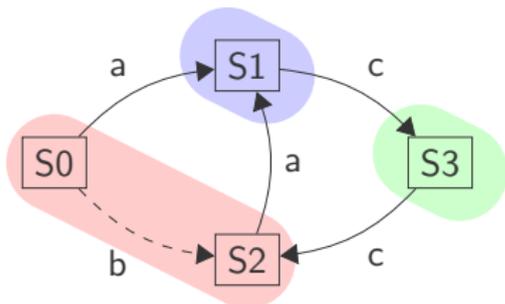
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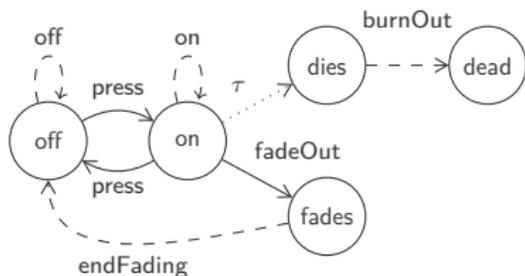
- Only works when the similarity relation is an equivalence
- Does not provide error trace when system is not proper

# 3-Valued Deterministic Finite Automaton

- A 3DFA is a tuple  $\langle \Sigma, S, s_0, \delta, Acc, Rej, Dont \rangle$
- $\mathcal{C}^+$  denotes the DFA  $\langle \Sigma, S, s_0, \delta, Acc \cup Dont \rangle$
- $\mathcal{C}^-$  denotes the DFA  $\langle \Sigma, S, s_0, \delta, Acc \rangle$
- A **consistent** DFA  $\mathcal{A}$  is such as  $\mathcal{L}(\mathcal{C}^-) \subseteq \mathcal{L}(\mathcal{A}) \subseteq \mathcal{L}(\mathcal{C}^+)$

# Categorizing behaviour

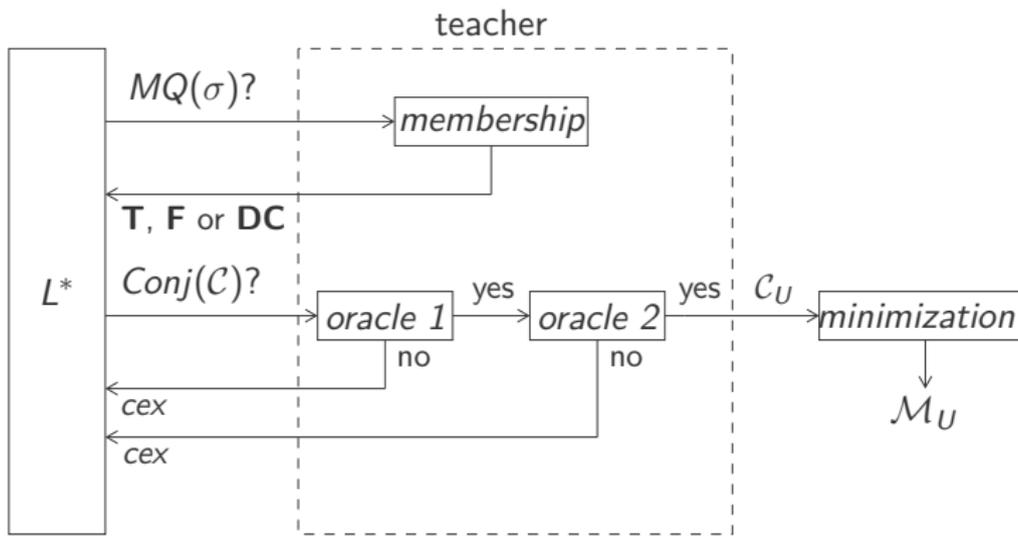
- Behaviour from the system can be categorized into three sets:
  - Accepted behaviour must be known
  - Rejected behaviour must be avoided
  - Don't care behaviour



- $\langle \text{press}, \text{press} \rangle \in \text{Acc}$
- $\langle \text{press}, \text{fadeOut}, \text{press} \rangle \in \text{Rej}$
- $\langle \text{press}, \text{endFading} \rangle \in \text{Dont}$

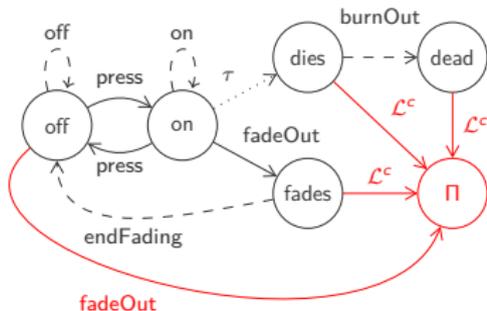
# Learning-Based Approach

- Using a **learning algorithm** to learn a 3DFA capturing all the possible full-control system abstractions (variant of  $L^*$ )



# Membership query

- **Completed system:** Adding  $s \xrightarrow{\alpha} \Pi$  for each  $\alpha \in \mathcal{L}^c \setminus A^c(s)$
- Given a sequence  $\sigma$ , it is simulated on the completed system and:
  - $\sigma$  may lead to the error state:  $MQ(\sigma) = \mathbf{F}$
  - $\sigma$  can be simulated entirely and never leads to an error state:  $MQ(\sigma) = \mathbf{T}$
  - $\sigma$  cannot be simulated entirely:  $MQ(\sigma) = \mathbf{DC}$



# Conjecture

- Two oracles :

**1 No invalid traces:** complete  $\mathcal{M}_{weak}$  on commands

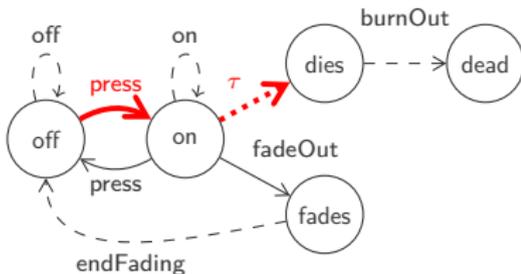
$$\mathcal{C}^+ \parallel (\mathcal{M}_{weak} + s \xrightarrow{\mathcal{L}^c \setminus A^c(s)} \Pi) \xRightarrow{\sigma} ? \quad \Pi$$

**2 All valid traces:** complete  $\mathcal{C}^-$  on commands and observations

$$(\mathcal{C}^- + s \xrightarrow{\mathcal{L} \setminus A(s)} \Pi) \parallel \mathcal{M}_{weak} \xRightarrow{\sigma} ? \quad \Pi$$

# Full-control determinism

- System abstraction generation will fail for systems which are not **full-control deterministic**
- After the execution of the same trace, the enabled commands are not the same



- After executing  $\langle \text{press} \rangle$ , reaching:
  - "on" where press and fadeOut are enabled
  - "dies" where no commands are enabled

- Framework implemented within JavaPathfinder model checker
- Details presented at the JPF Workshop

# Experiments

	System	Abstraction	Reduc.	Learning	
	States / Trans.	States / Trans.		3DFA states	Total
<b>VTS</b>	8 / 20	5 / 14	10 ms	10	92 ms
<b>AirConditionner</b>	154 / 885	27 / 150	177 ms	51	6 271 ms
<b>TimedVCR</b>	3 352 / 15 082	2 / 9	1 031 ms	6	614 ms
<b>SimpleVCR</b>	20 / 110	2 / 9	65 ms	6	250 ms
<b>FullVCR</b>	24 / 261	4 / 24	45 ms	11	432 ms
<b>AlarmClock</b>	42 / 215	5 / 14	–	14	512 ms
<b>AlarmClock2</b>	1 734 / 67 535	5 / 15	–	14	30 831 ms

- Reduction-based vs. learning-based: no clear winner
- Learning can handle more system models

# Conclusion and further work

## ■ Conclusion

- A new method based on learning for generation full-control system abstraction
- Implemented in a framework based on JavaPathfinder model checker
- The framework can be used to detect mode confusion

## ■ Further work

- Experiment with more realistic examples
- Experiment with variant of full-control property
  - allow the user to ignore some commands
  - integrate a “task model”
- Revisit the reduction-based approach