

## 9. Temporal logic

For a transition system  $G$  with state set  $\Sigma$  and initial state set  $I$ ,  $G$  satisfies a temporal logic formula  $\psi$ , written as  $G \models \psi$ , if  $\psi$  holds in all initial states of  $G$ , i.e. if

$$I \subseteq \llbracket \psi \rrbracket = \{x \in \Sigma \mid x \models \psi\}$$

The set  $\llbracket \psi \rrbracket$  can be determined by  $\mu$ -calculus.

Ex



Evaluate the nonblocking condition  $\llbracket \forall \square \exists \Diamond p \rrbracket$ , where the state label  $\{p\}$  determines a marked state.

$$\text{since } \exists \Diamond p \equiv \mu z. p \vee \exists 0z$$

$$\forall \square q \equiv \nu y. q \vee \forall 0y$$

$$\forall \square \exists \Diamond p \equiv \nu y. (\mu z. p \vee \exists 0z) \vee \forall 0y$$

$$\llbracket \mu z. p \vee \exists 0z \rrbracket = \mu z. \Psi(z)$$

where  $\Psi(z) = \llbracket p \rrbracket \cup \text{Pre}^\exists(z) = z$

Least fixed point:

$$z_{i+1} = \Psi(z_i), \quad z_0 = \emptyset$$

$$Z_1 = \Psi(Z_0) = \llbracket p \rrbracket \cup \text{Pre}^{\exists}(Z_0) = \{2\} \cup \emptyset = \{2\}$$

$$Z_2 = \llbracket p \rrbracket \cup \text{Pre}^{\exists}(Z_1) = \{2\} \cup \{0\} = \{0, 2\}$$

$$Z_3 = \{2\} \cup \text{Pre}^{\exists}(\{0, 2\}) = \{2\} \cup \{0\} = \{0, 2\} = Z_2 = \text{fixed point } Z^w$$

$$\llbracket \forall \Diamond \exists \Diamond p \rrbracket = \bigvee Y. \Psi(Y)$$

$$\text{where } \Psi(Y) = \llbracket M \models p \vee \exists 0 \in Z \rrbracket$$

$$\cap \text{Pre}^{\forall}(Y) = Z^w \cap \text{Pre}^{\forall}(Y) = Y$$

Greatest fixed point:

$$Y_{i+1} = \Psi(Y_i), \quad Y_0 = \overline{X}$$

$$Y_1 = Z^w \cap \text{Pre}^{\forall}(\overline{X}) = \{0, 2\} \cap \{0, 1, 2\} = \{0, 2\}$$

$$Y_2 = Z^w \cap \text{Pre}^{\forall}(Y_1) = \{0, 2\} \cap \{2\} \leftarrow (0 \text{ is excluded since its target state } 1 \text{ is not included in } Y_1 = \{0, 2\}) = \{2\}$$

$$Y_3 = Y_2 = \text{fixed point } Y^w$$

$$I = \{0\} \not\subseteq \llbracket \forall \Diamond \exists \Diamond p \rrbracket = Y^w = \{2\}$$

$$\Rightarrow G \not\models \forall \Diamond \exists \Diamond p$$

Remove state   $\Rightarrow$

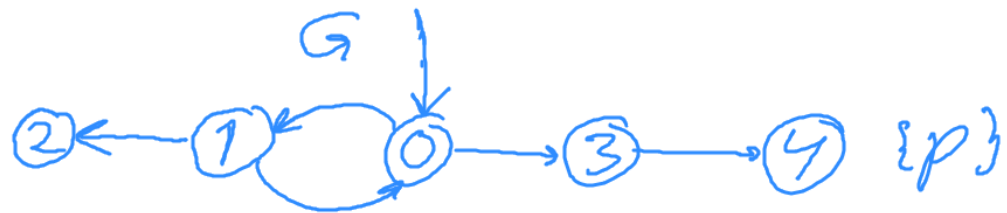
$$Z^w = \{0, 2\} \quad Y_1 = Y_2 = Y^w = \{0, 2\}$$

$$\Rightarrow I \subseteq Y^w \text{ and } G \models \forall \Diamond \exists \Diamond p.$$

Correct since state 2 is a blocking state.

Removing this blocking state  
 $\Rightarrow G$  is nonblocking and satisfies  
 the nonblocking condition  $\forall \Box \exists \Diamond p$

Ex



Evaluate again the nonblocking  
 condition  $\forall \Box \exists \Diamond p$

$\llbracket \exists \Diamond p \rrbracket = \mu Z. \Psi(Z)$  where

$$\Psi(Z) = \llbracket p \rrbracket \cup \text{Pre}^{\exists}(Z) = Z$$

Least fixed point iteration:

$$Z_0 = \emptyset, \quad Z_1 = \llbracket p \rrbracket \cup \text{Pre}^{\exists}(\emptyset) = \{4\} \cup \emptyset$$

$$\begin{aligned} Z_2 &= \llbracket p \rrbracket \cup \text{Pre}^{\exists}(\{4\}) = \\ &= \{4\} \cup \{3\} = \{3, 4\} \end{aligned}$$

$$\begin{aligned} Z_3 &= \llbracket p \rrbracket \cup \text{Pre}^{\exists}(\{3, 4\}) = \{4\} \cup \{0, 3\} = \\ &= \{0, 3, 4\} \end{aligned}$$

$$Z_4 = \{4\} \cup \{1, 0, 3\} = \{0, 1, 3, 4\}$$

$$Z_5 = Z_4 = \text{fixed point } Z^w = \{0, 1, 3, 4\}$$

$$\llbracket \forall \Box \exists \Diamond p \rrbracket = \bigvee Y. Z^w \cap \text{Pre}^{\forall}(Y)$$

Greatest fixed point iteration:

$$\begin{aligned} Y_0 &= \Sigma, \quad Y_1 = Z^w \cap \text{Pre}^{\forall}(\Sigma) = \\ &= Z^w \cap \Sigma = Z^w = \{0, 1, 3, 4\} \end{aligned}$$

$$Y_2 = Z^w \cap \text{Pre}^{\forall}(\underbrace{\{0, 1, 3, 4\}}_{Y_1}) =$$

$= Z^w \cap \{0, 3, 4\} = (\text{state 1 excluded since its target state is not included in } Y_1 \text{ in } \text{Pre}^V(Y_1)) = \{0, 3, 4\}$

$$Y_3 = Z^w \cap \text{Pre}^V(\underbrace{\{0, 3, 4\}}_{Y_2}) = \{3, 4\}$$

since the target state 1 of state 0 not included in  $Y_2$

$$Y_4 = Y_3 = \text{fixed point } Y^w = \{3, 4\}$$

$$I = \{0\} \neq Y^w = \llbracket \forall \Box \Diamond p \rrbracket \Rightarrow$$

$$G \neq \forall \Box \Diamond p$$

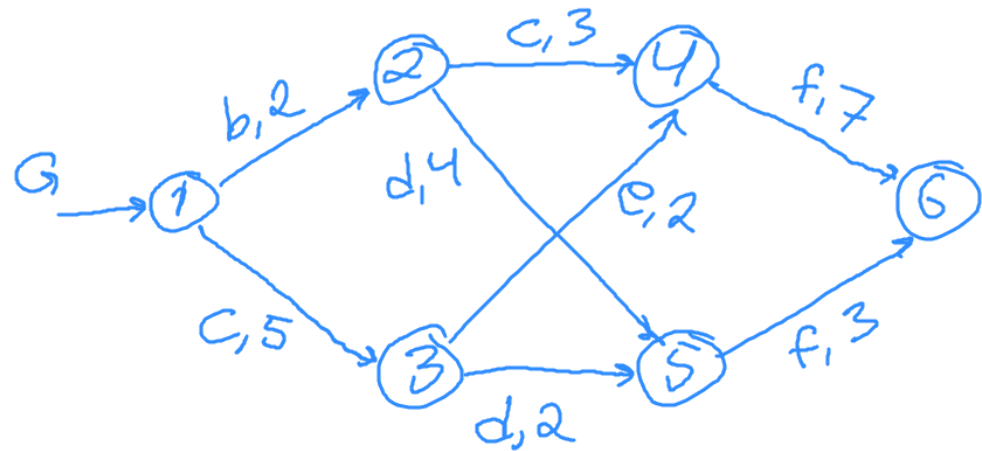
## 10. Reinforcement learning (RL)

RL = optimization method where actions are sent to the plant and resulting rewards are evaluated such that optimal actions are selected after an initial learning phase. Currently a very popular method within modern AI and machine learning.

AlphaGo is a popular program where its success is based on RL.

The optimization in RL is a minor reformulation of Dynamic Programming

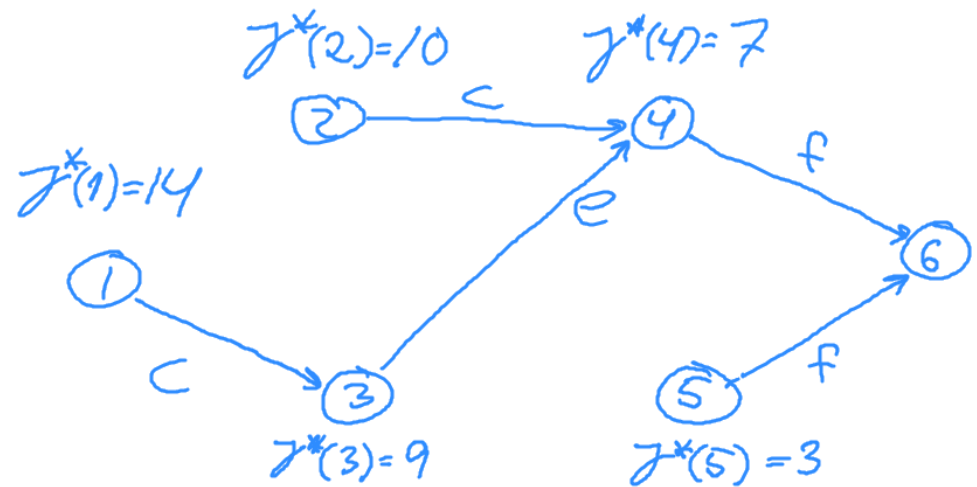
Rewards are then introduced on the transitions in an automaton.



Reward function  $P: \mathcal{X} \times \mathcal{Z} \rightarrow \mathbb{R}$   
 $P(1,b)=2, P(1,c)=5, P(2,c)=3, \dots$

Optimization

$$J^*(x_n) = \max_{\{a_n, \dots, a_1\}} \sum_{i=k}^{N-1} P(x_i, a_i)$$



Optimal actions:  $a(1)=c, a(2)=c$   
 $a(3)=e, a(4)=f, a(5)=f$