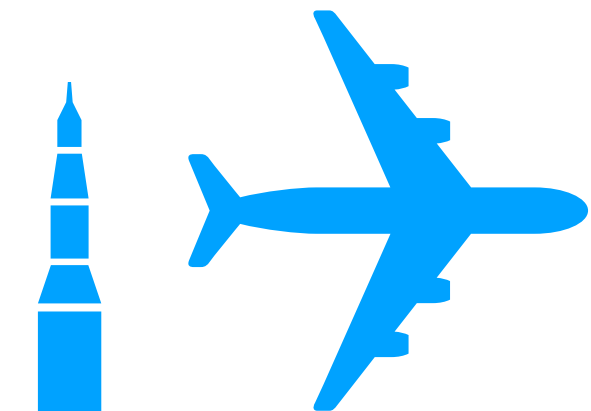
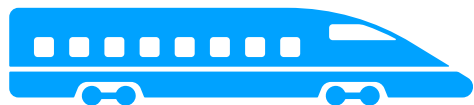
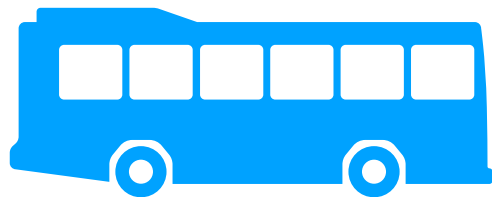


# Quantitative Games on Graphs

Benjamin Monmege, Aix-Marseille Université

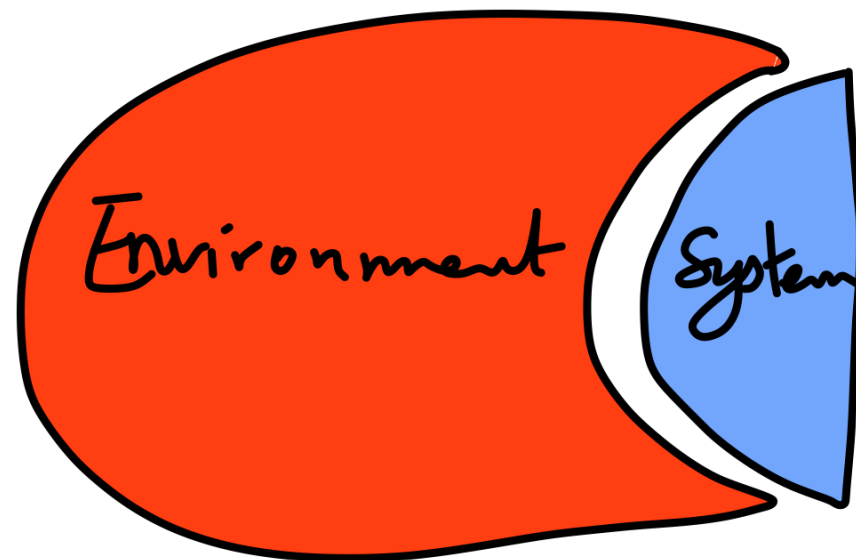
Séminaire ENS Rennes

# Games for synthesis



*Reactive  
systems*

Crucial to make the critical programs **correct**



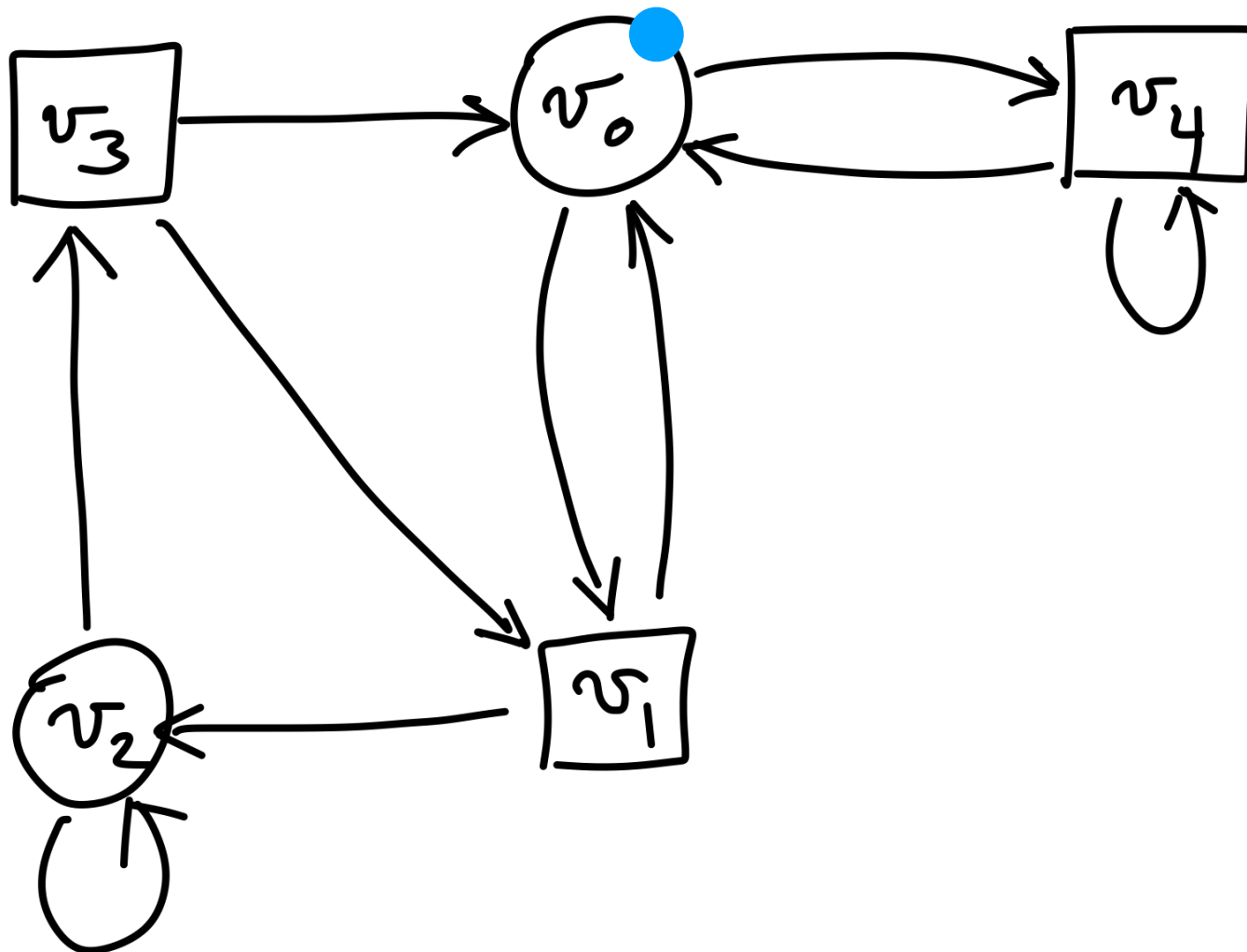
$\models$  *Specification*

Instead of verifying an existing system...

**Synthesise** a correct-by-design one!

**Winning strategy = Correct system**

# 2-player zero-sum games on graphs



Finite directed graphs

Vertices of Player  $\bigcirc$

Vertices of Player  $\square$

**Play:** move a token along vertices

**Infinite number of rounds**

Outcome: infinite path

$v_0 \longrightarrow v_1 \longrightarrow v_0 \longrightarrow v_4 \longrightarrow v_0 \dots$

# Who is winning?

$$\text{Win}_O \subseteq V^\omega$$

set of good outcomes for Player 1

$$\text{Win}_\square = V^\omega \setminus \text{Win}_O$$

(zero-sum game)

Examples of winning conditions:

$$\text{Win}_O = \{\pi \mid \pi \text{ visits } \text{Good}\}$$

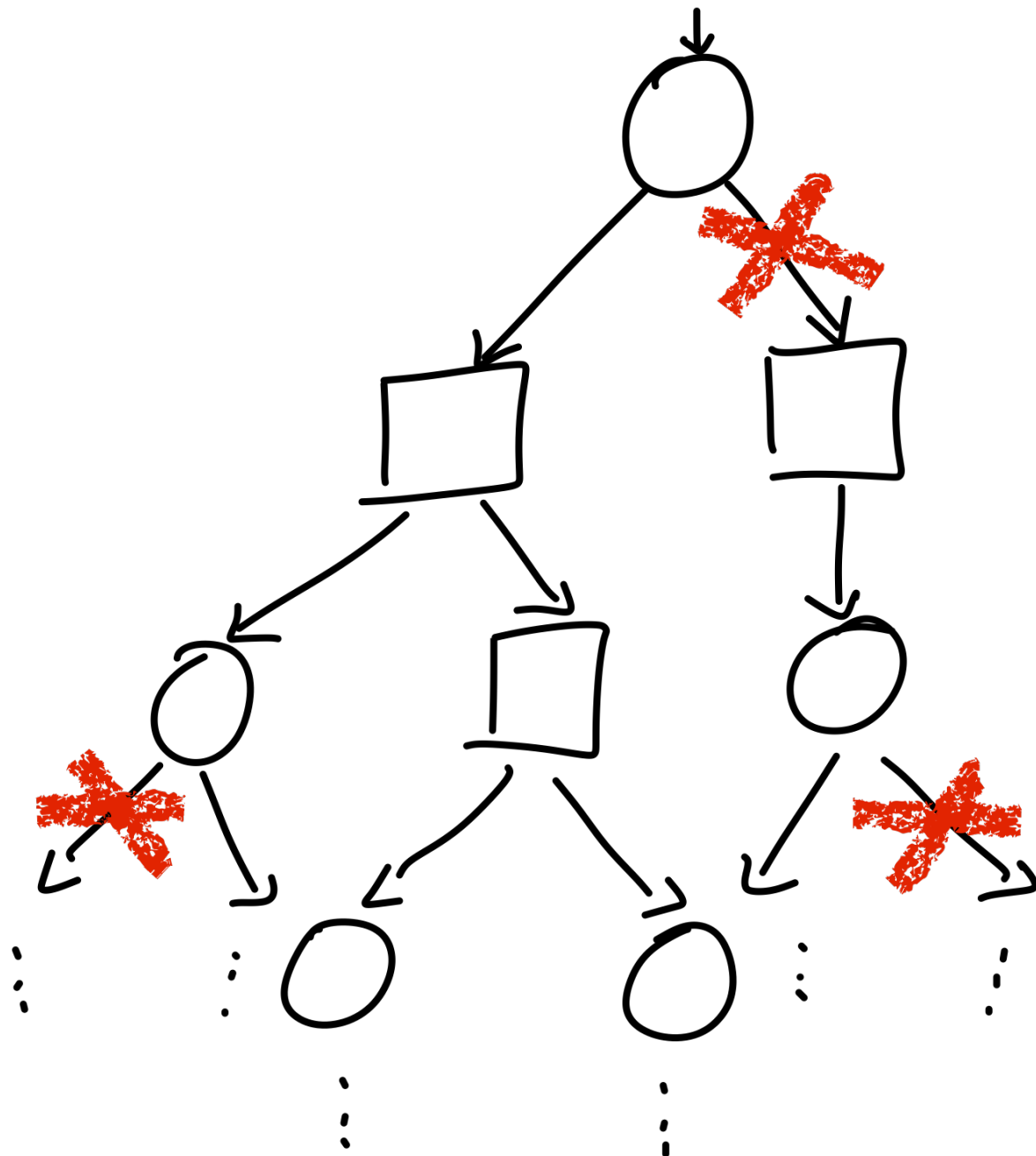
reachability

$$\text{Win}_O = \{\pi \mid \pi \text{ visits } \text{Good} \text{ infinitely often}\}$$

Büchi

# Strategies

Unfolding of the game graph:



**Strategy for Player  $\bigcirc$ :** one choice in each node of Player  $\bigcirc$  in unfolding

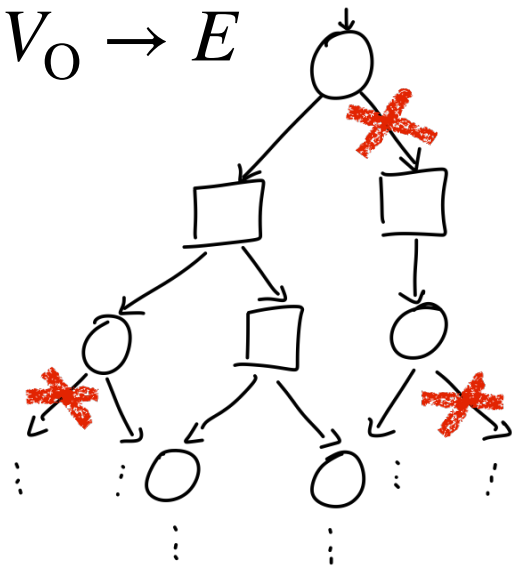
$$\sigma_O : V^* V_O \rightarrow E$$

Strategy is **winning** if **all paths** of the resulting tree are winning

# Types of strategies

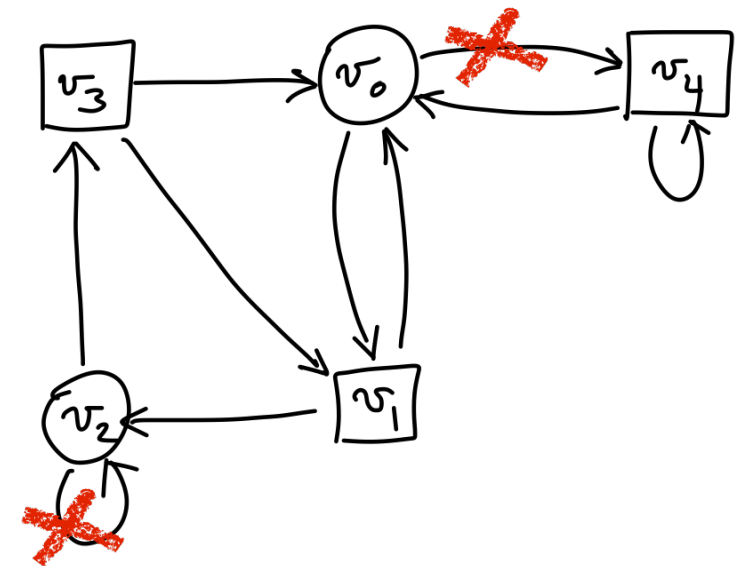
## Strategy (infinite memory)

$$\sigma_O: V^*V_O \rightarrow E$$



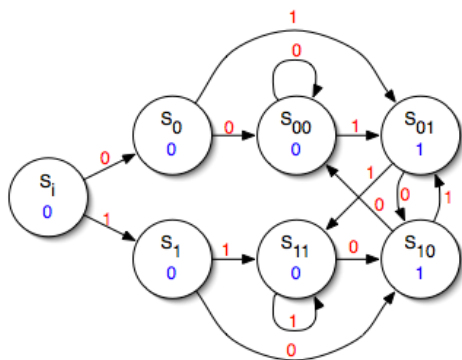
## Memoryless/positional strategy

$$\sigma_O: V_O \rightarrow E$$



## Finite memory strategy

$$\sigma_O: V^*V_O \rightarrow E \text{ representable with a Moore machine}$$



## Randomised strategy

$$\sigma_O: V^*V_O \rightarrow \text{Distr}(E)$$



# Decision problem

Given a game graph  $G$  and a winning condition  $\text{Win}_O$   
decide if Player  $\bigcirc$  has a winning strategy.

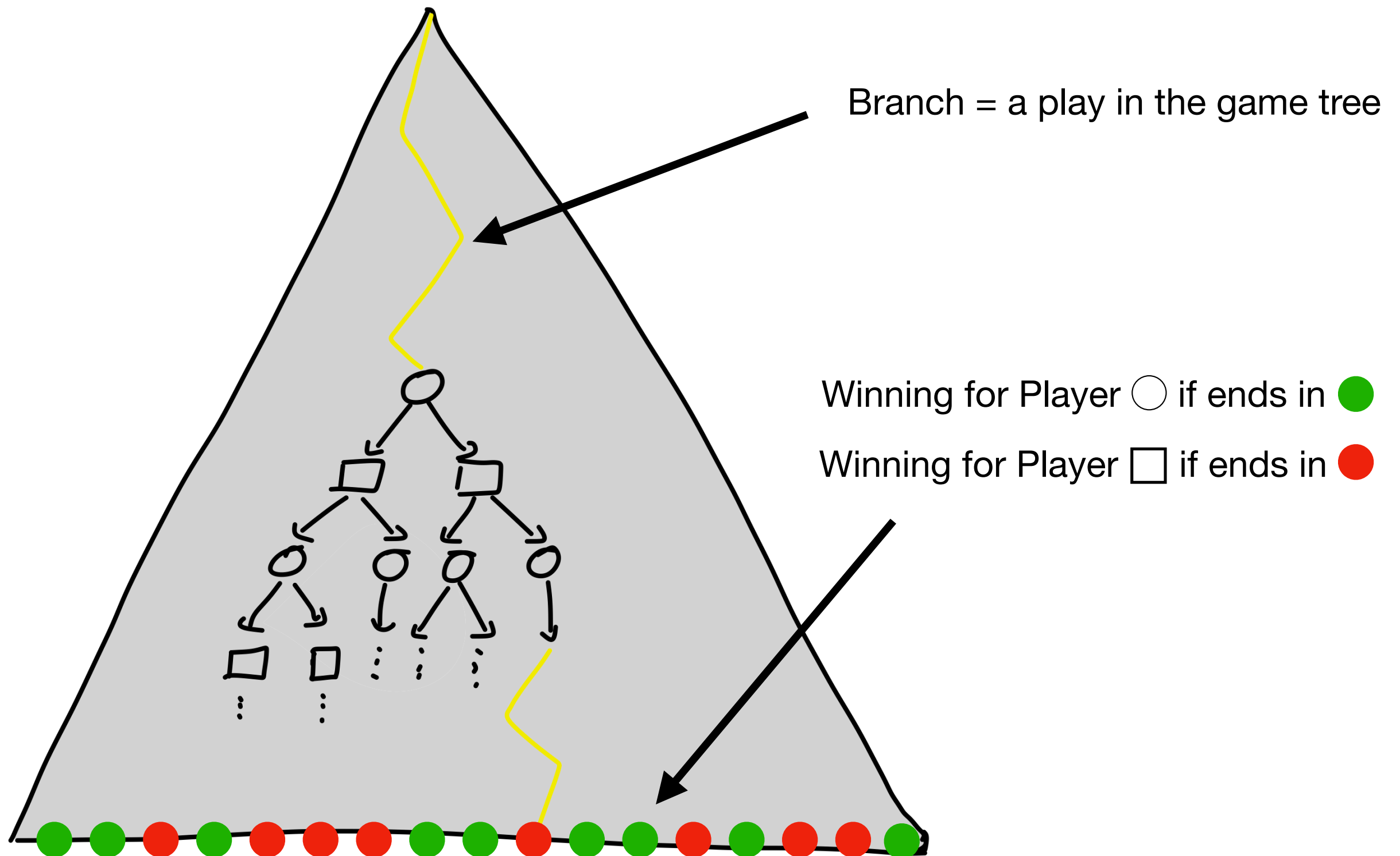
**What about Player  $\square$ ?**

Determinacy (true in a large class of objectives, e.g. all  $\omega$ -regular objectives)

**either** Player  $\bigcirc$  has a winning strategy for  $\text{Win}_O$

**or** Player  $\square$  has a winning strategy for  $\text{Win}_\square = V^\omega \setminus \text{Win}_O$

# Example: finite trees





# Example: finite trees

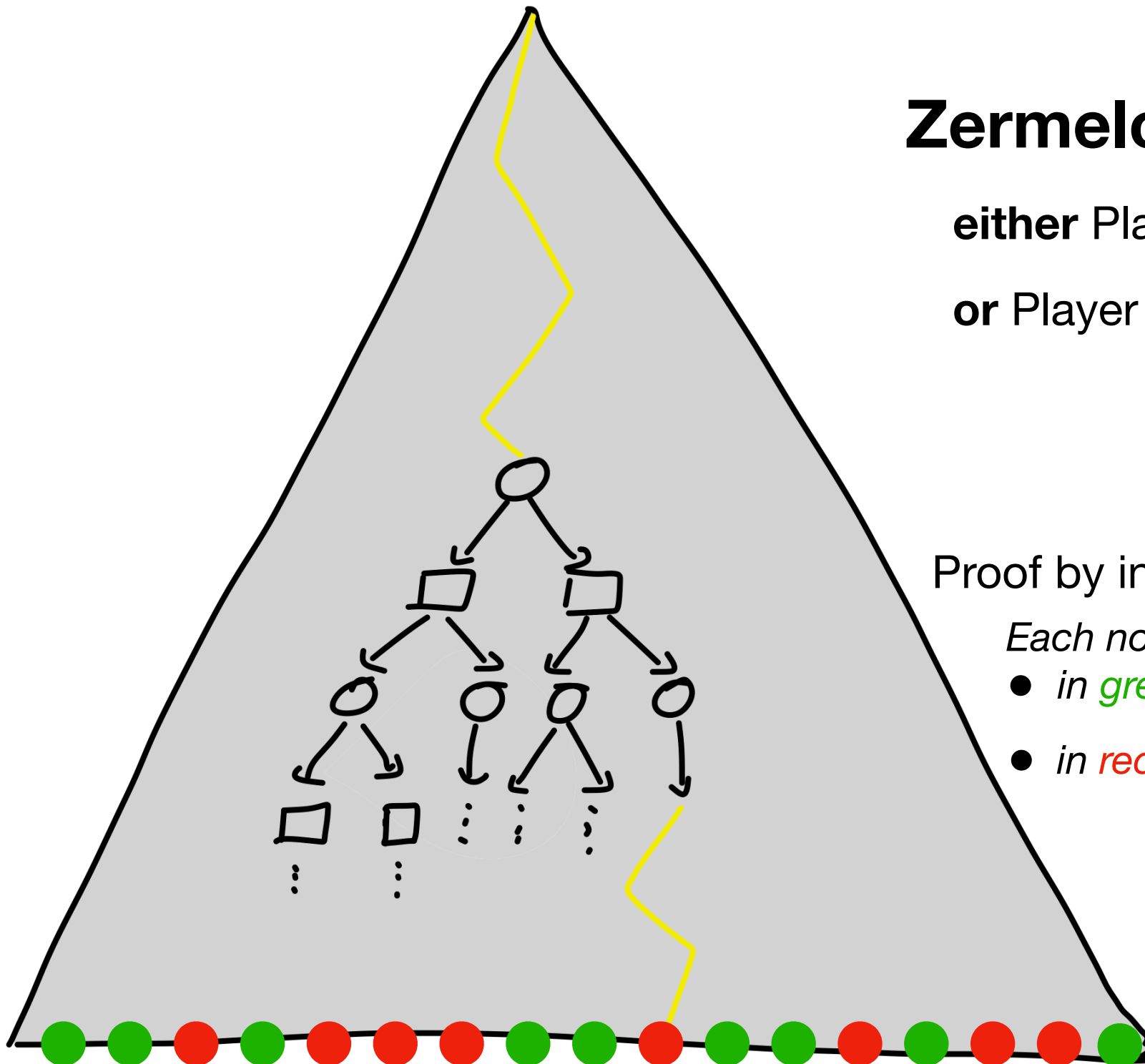
## Zermelo's theorem

either Player  $\bigcirc$  has a strategy to force  $\bullet$   
or Player  $\square$  has a strategy to force  $\bullet$   
= **determinacy**

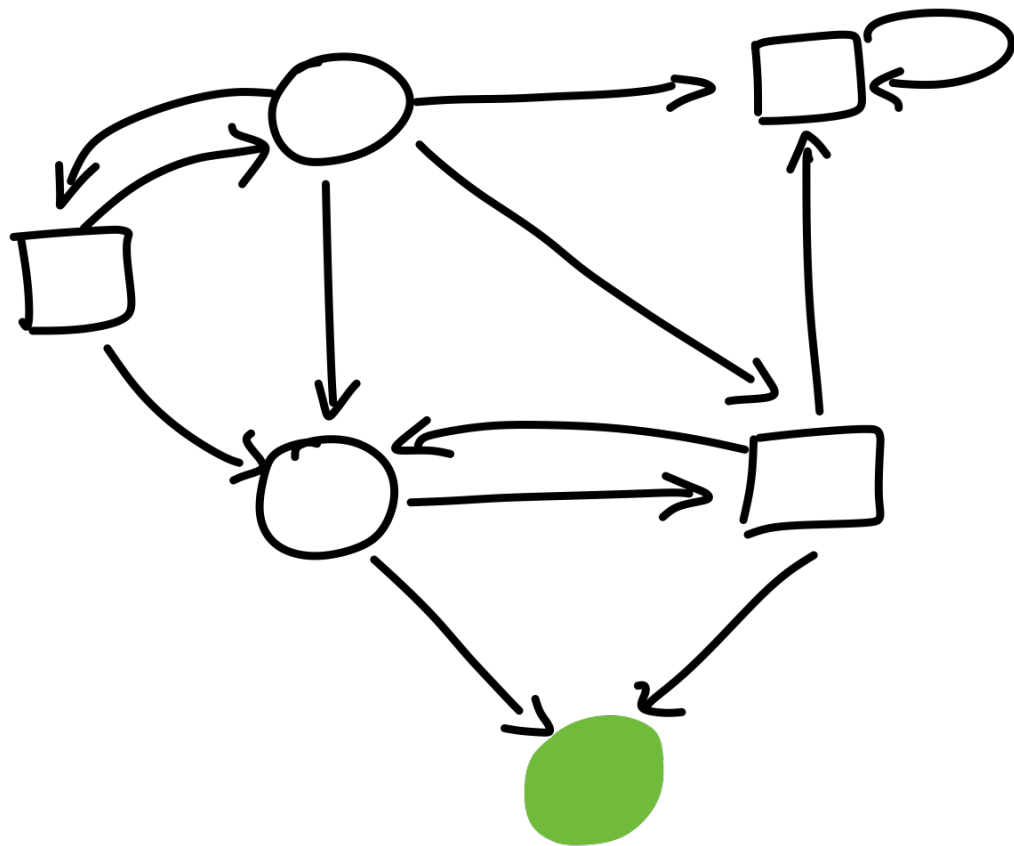
Proof by induction on the depth of the tree

*Each node can be labelled bottom-up:*

- in *green* if Player  $\bigcirc$  can force  $\bullet$  from there
- in *red* if Player  $\square$  can force  $\bullet$  from there



# Example: reachability in graphs



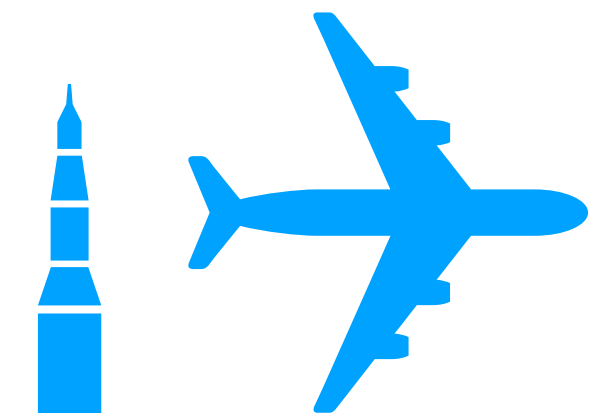
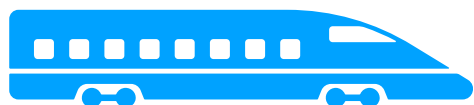
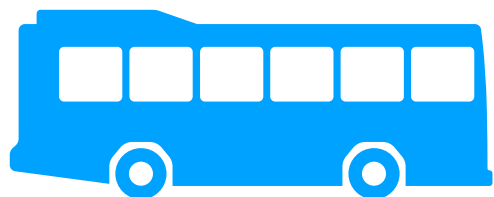
$$\text{Win}_O = \{ \pi \mid \pi \text{ visits } \text{Good} \}$$

$$\text{Win}_\square = \{ \pi \mid \pi \text{ avoids } \text{Good} \}$$

Apply the same bottom-up rule...

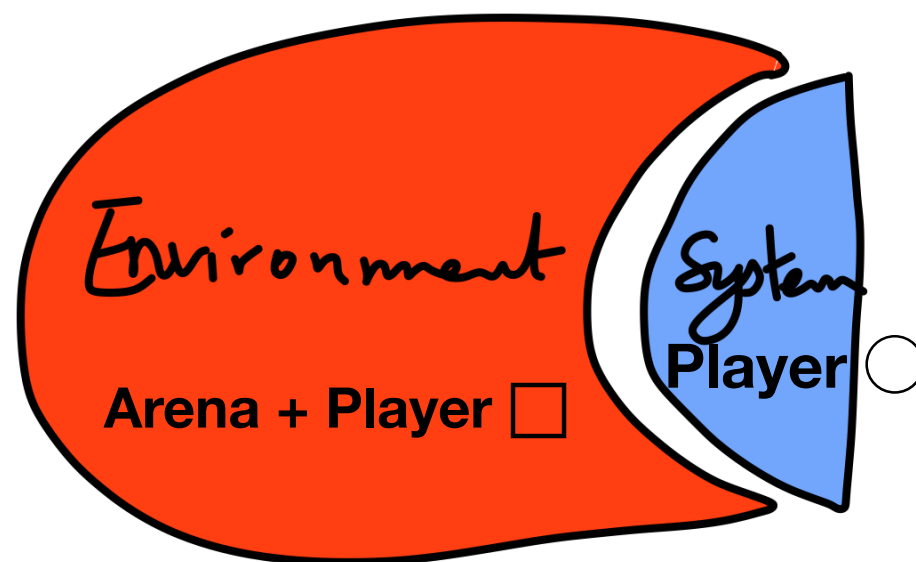
...to decide the winner and find winning strategies

# Games for synthesis



Reactive  
systems

Crucial to make the critical programs **correct**



$\models$  Specification

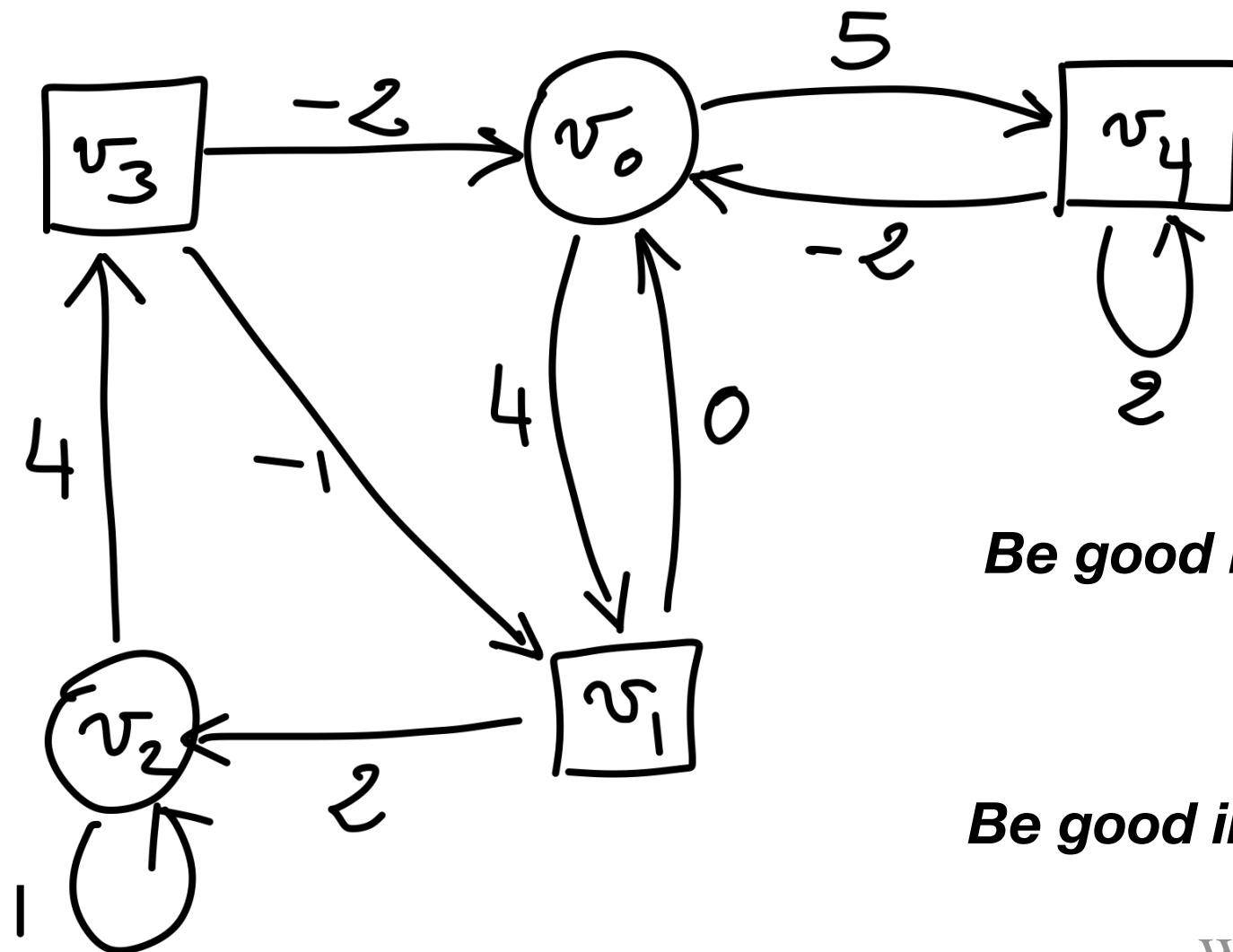
Winning condition

Instead of

What if several winning strategies for Player  $\circ$ ?  
Need for a quality measure, to choose the best one...

Winning strategy = Correct system

# Quantitative games on graphs



**Weighted graph:** weights=rewards

**Be good in total:** total-payoff

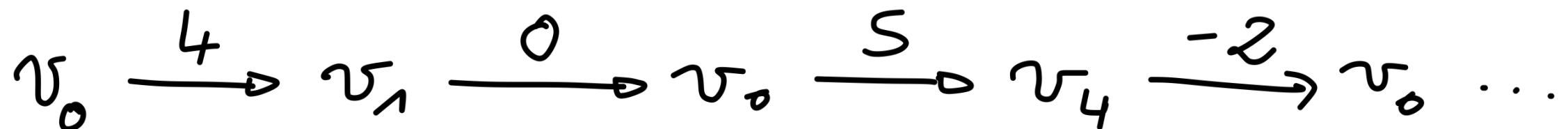
$$\sum_{i=0}^{\infty} r_i$$

may not exist...

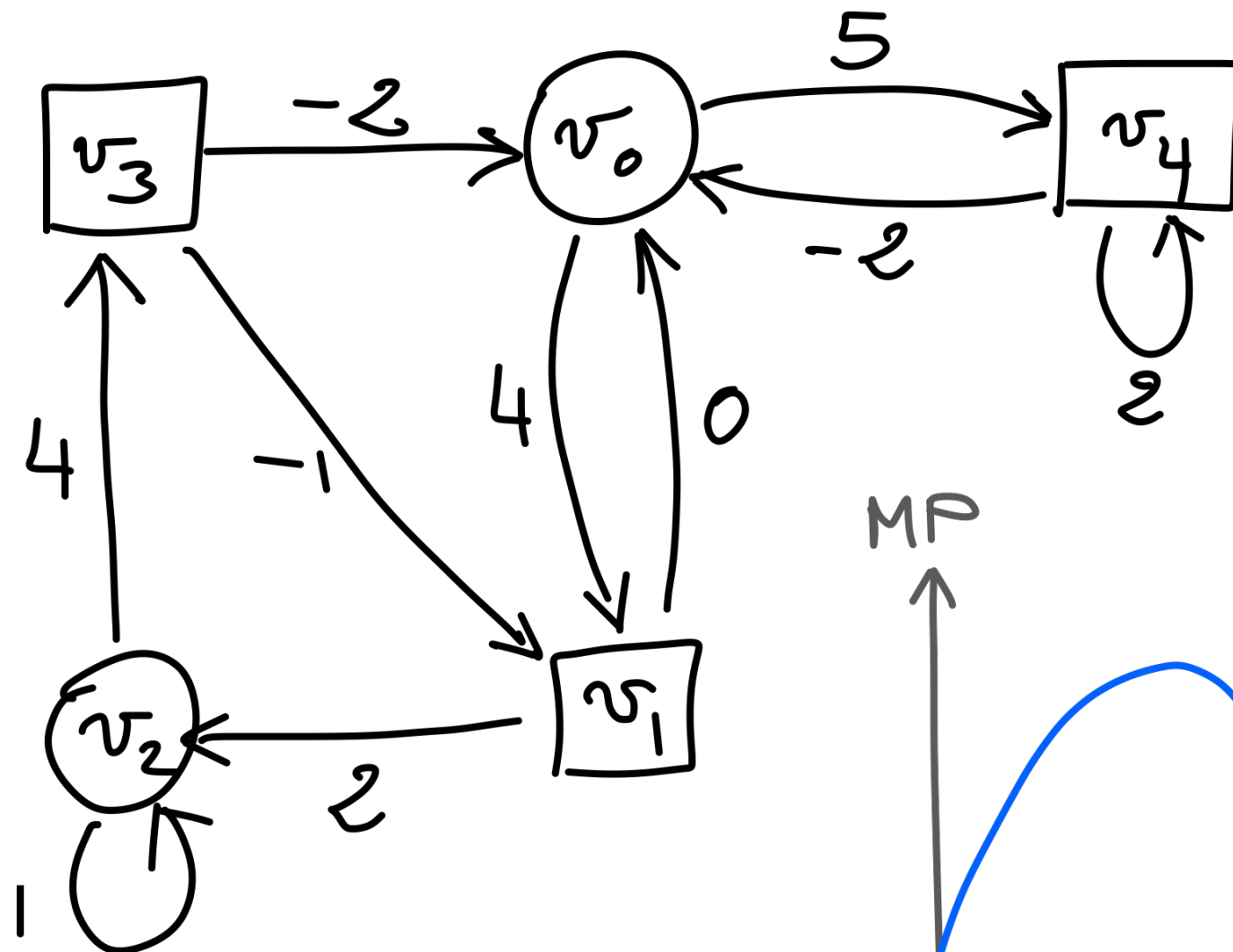
**Be good in average:** mean-payoff

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \sum_{i=0}^{n-1} r_i$$

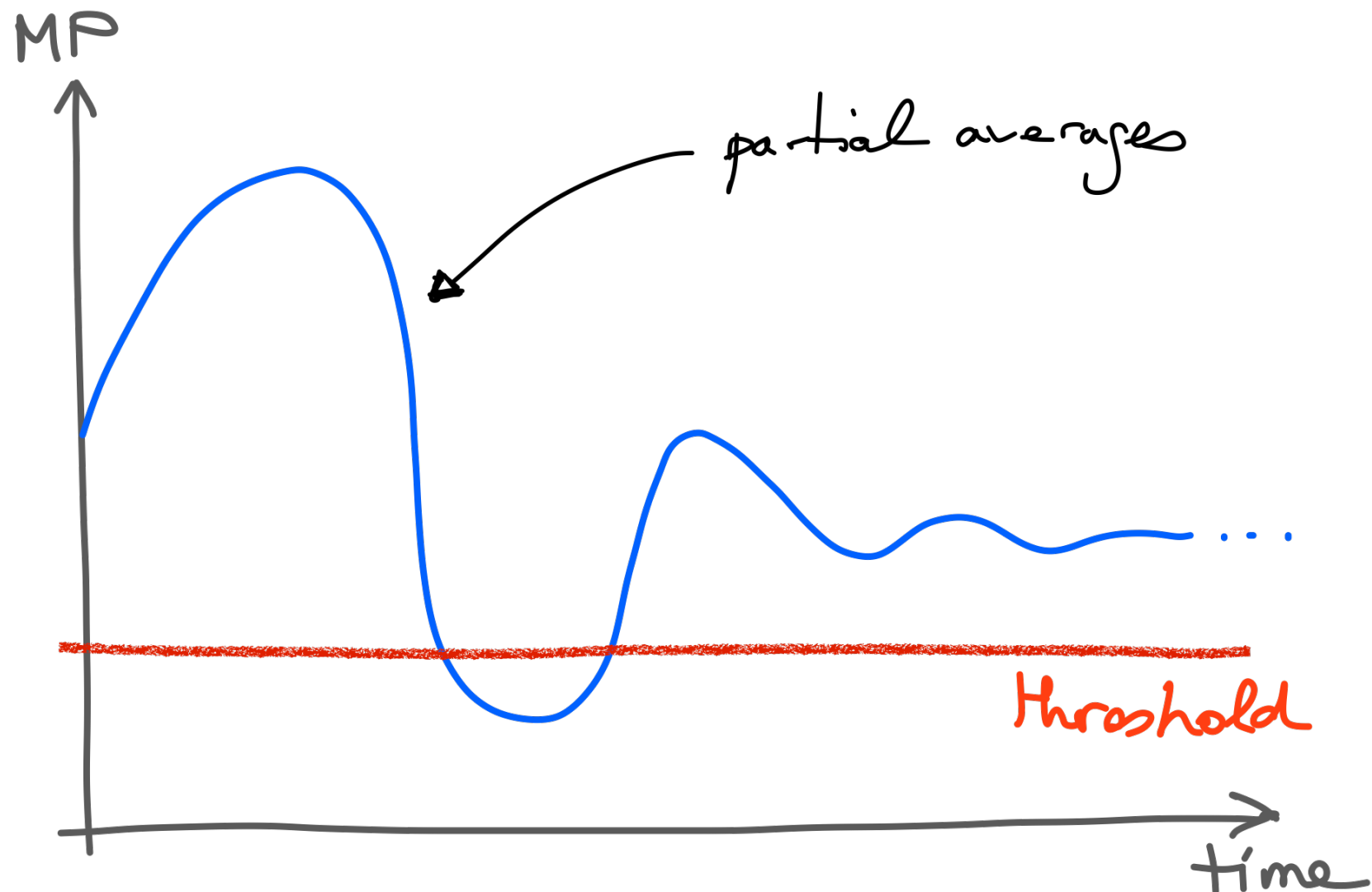
$\text{Win}_O = \{\pi \mid \text{MP}(\pi) \geq c\}$  not  $\omega$ -regular...



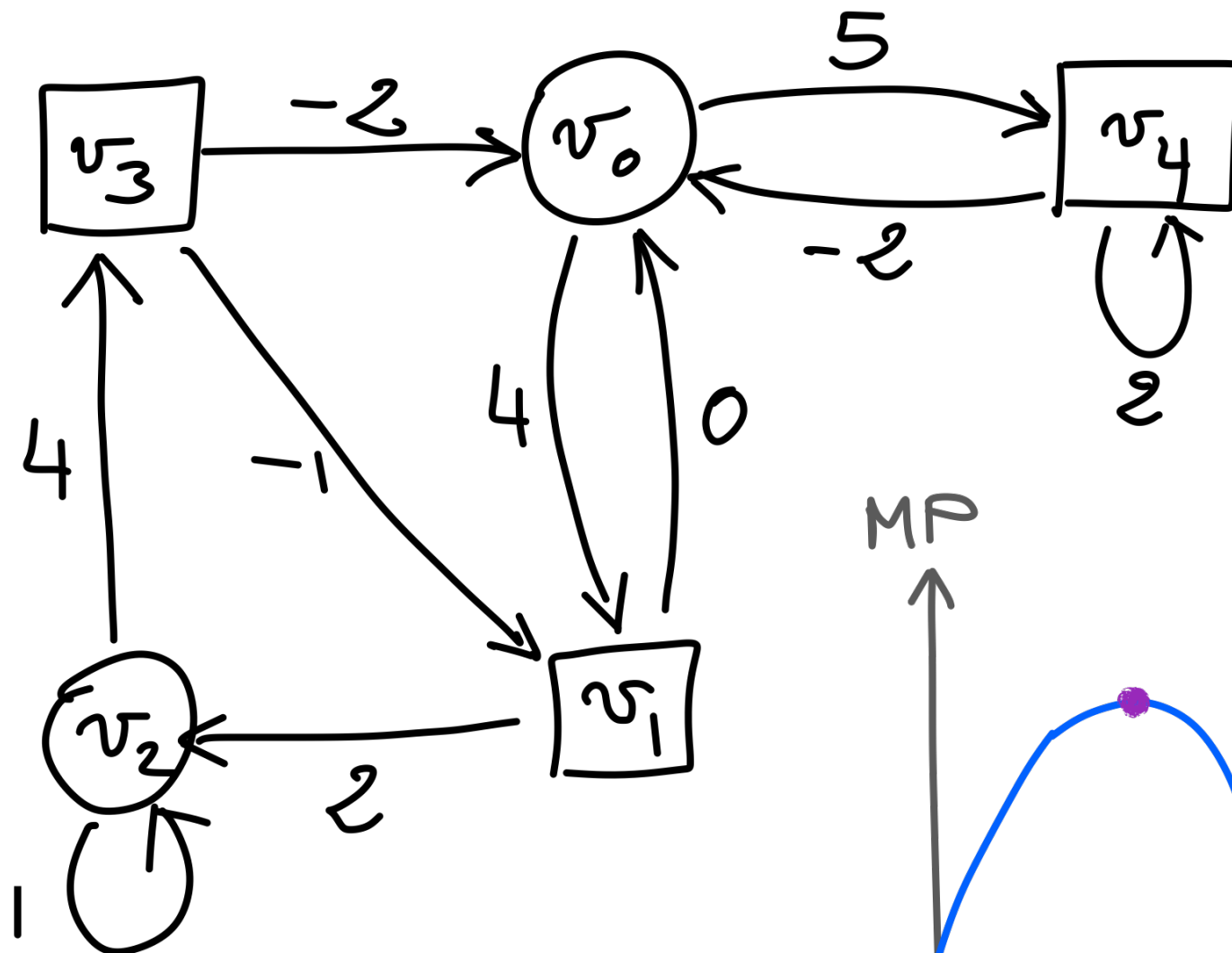
# Mean-payoff games



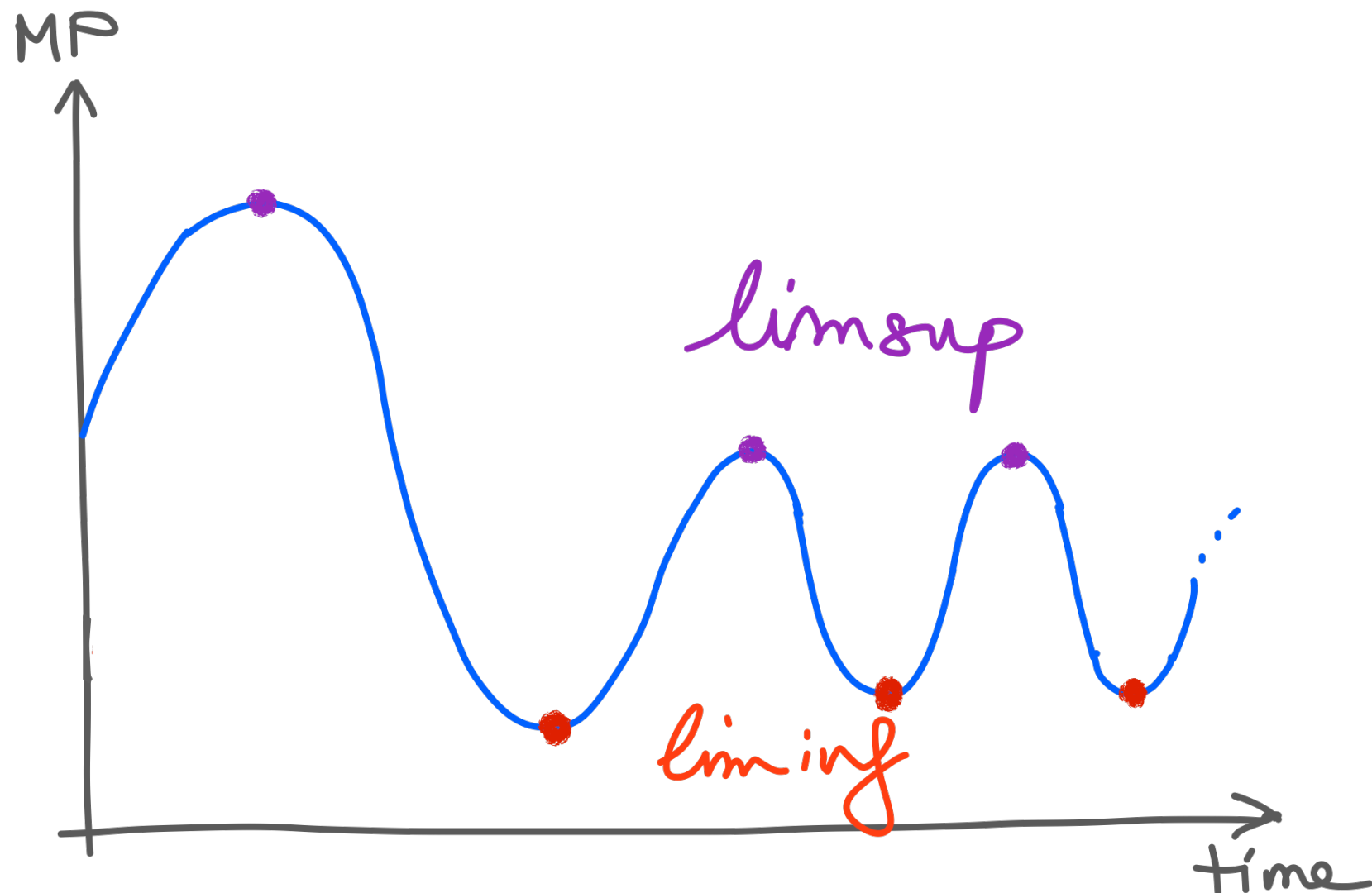
Be good in average:  $\liminf_{n \rightarrow \infty} \frac{1}{n} \sum_{i=0}^{n-1} r_i$



# Mean-payoff games



*Be good in average:*  $\liminf_{n \rightarrow \infty} \frac{1}{n} \sum_{i=0}^{n-1} r_i$



# Mean-payoff games

Greatest mean-payoff that Player  $\bigcirc$  can guarantee:

$$\text{Val}_{\bigcirc}(v) = \inf_{\sigma_{\square}} \sup_{\sigma_{\bigcirc}} \text{MP}(\text{play}(v, \sigma_{\bigcirc}, \sigma_{\square}))$$

Smallest mean-payoff that Player  $\square$  can guarantee:

$$\text{Val}_{\square}(v) = \sup_{\sigma_{\bigcirc}} \inf_{\sigma_{\square}} \text{MP}(\text{play}(v, \sigma_{\bigcirc}, \sigma_{\square}))$$

## Theorem (Ehrenfeucht-Mycielski 1979, Zwick-Paterson 1997)

1. Mean-payoff games are determined:  $\forall v \quad \text{Val}_{\bigcirc}(v) = \text{Val}_{\square}(v) =: \text{Val}(v)$

2. Both players have *optimal* memoryless strategies:

$$\exists \sigma_{\bigcirc}^* \forall v \quad \inf_{\sigma_{\square}} \text{MP}(\text{play}(v, \sigma_{\bigcirc}^*, \sigma_{\square})) = \text{Val}(v)$$

$$\exists \sigma_{\square}^* \forall v \quad \sup_{\sigma_{\bigcirc}} \text{MP}(\text{play}(v, \sigma_{\bigcirc}, \sigma_{\square}^*)) = \text{Val}(v)$$

3. The winner, with respect to a fixed threshold, can be decided in  $\text{NP} \cap \text{co-NP}$ .

# 1. Mean-payoff games are determined

$$\text{Val}_{\square}(v) = \sup_{\sigma_O} \inf_{\sigma_{\square}} \text{MP}(\text{play}(v, \sigma_O, \sigma_{\square})) \leq \inf_{\sigma_{\square}} \sup_{\sigma_O} \text{MP}(\text{play}(v, \sigma_O, \sigma_{\square})) = \text{Val}_O(v)$$

Determinacy (inequality  $\geq$ ) can be restated as:

$\forall \alpha$     **either** Player  $\bigcirc$  has a strategy to force a  $\text{MP} \geq \alpha$   
         **or** Player  $\square$  has a strategy to force a  $\text{MP} < \alpha$



# First-cycle game

Unfold the weighted graph up to a first repetition of vertex:

- a leaf is **winning for Player**  $\bigcirc$  if the cycle has a sum  $\geq 0$
- a leaf is **winning for Player**  $\square$  if the cycle has a sum  $< 0$

By Zermelo's theorem:

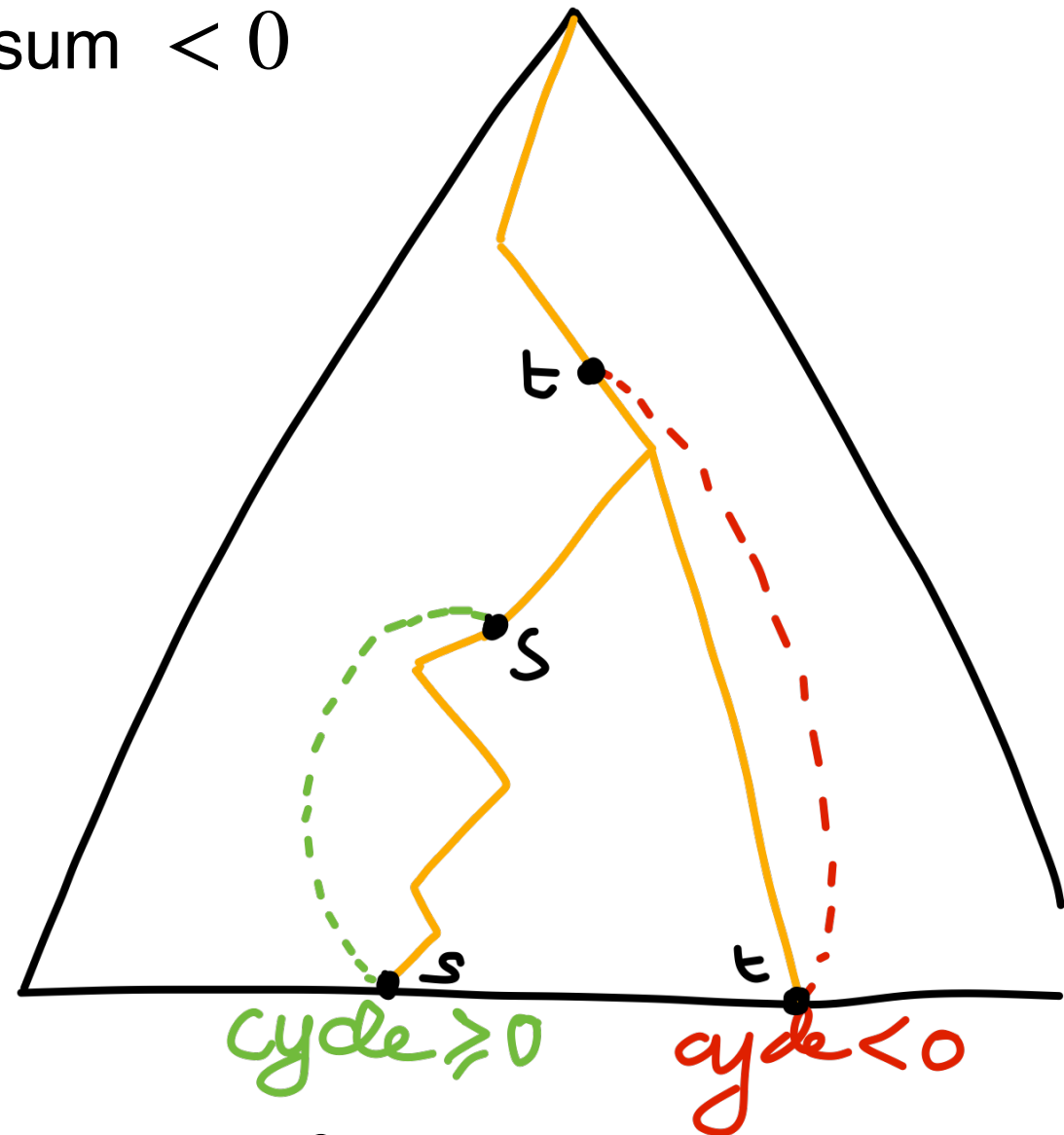
**either** Player  $\bigcirc$  can force **non-negative cycles**

**or** Player  $\square$  can force **negative cycles**

*transfer of strategies*

**either** Player  $\bigcirc$  has a memoryless strategy to force a MP  $\geq 0$

**or** Player  $\square$  has a memoryless strategy to force a MP  $< 0$



# Mean-payoff games

**Theorem (Ehrenfeucht-Mycielski 1979, Zwick-Paterson 1997)**

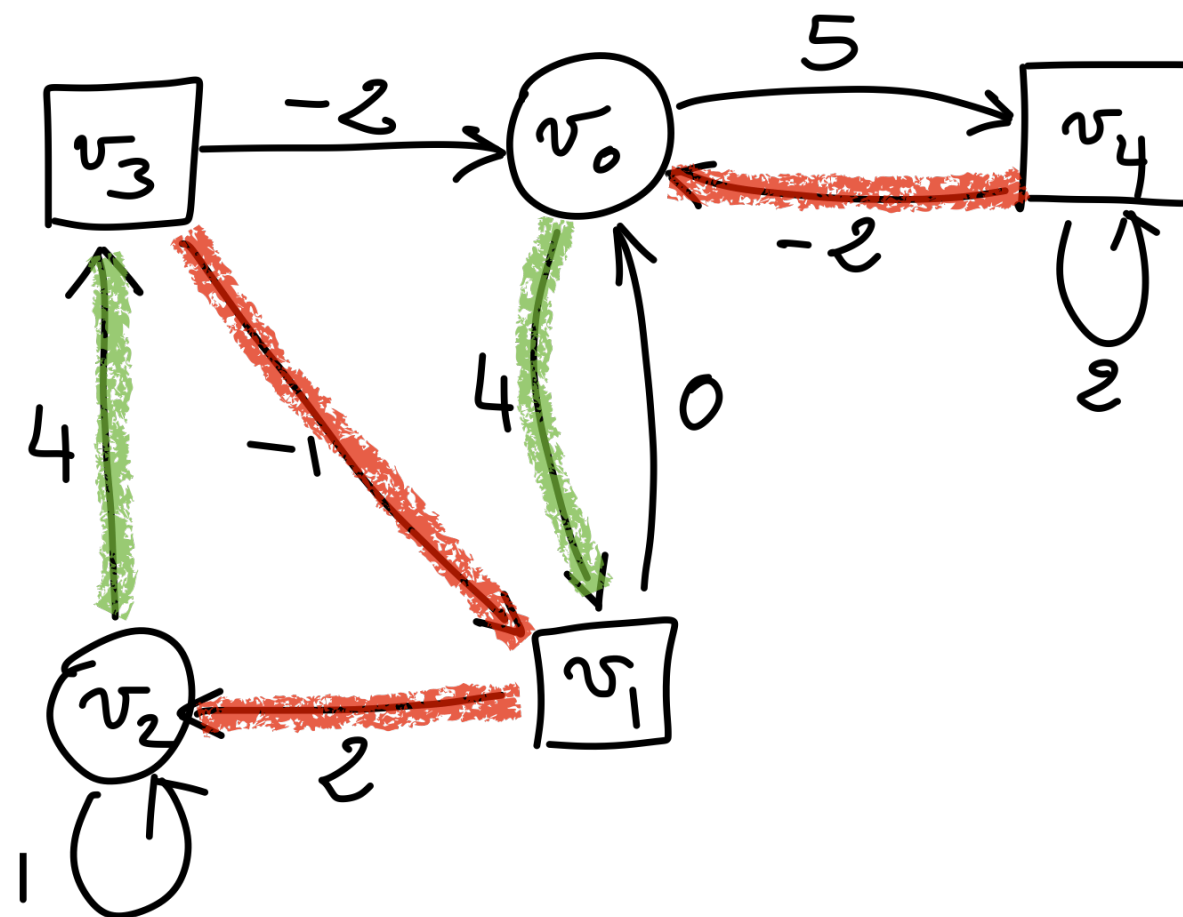
1. Mean-payoff games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$

2. Both players have *optimal* memoryless strategies:

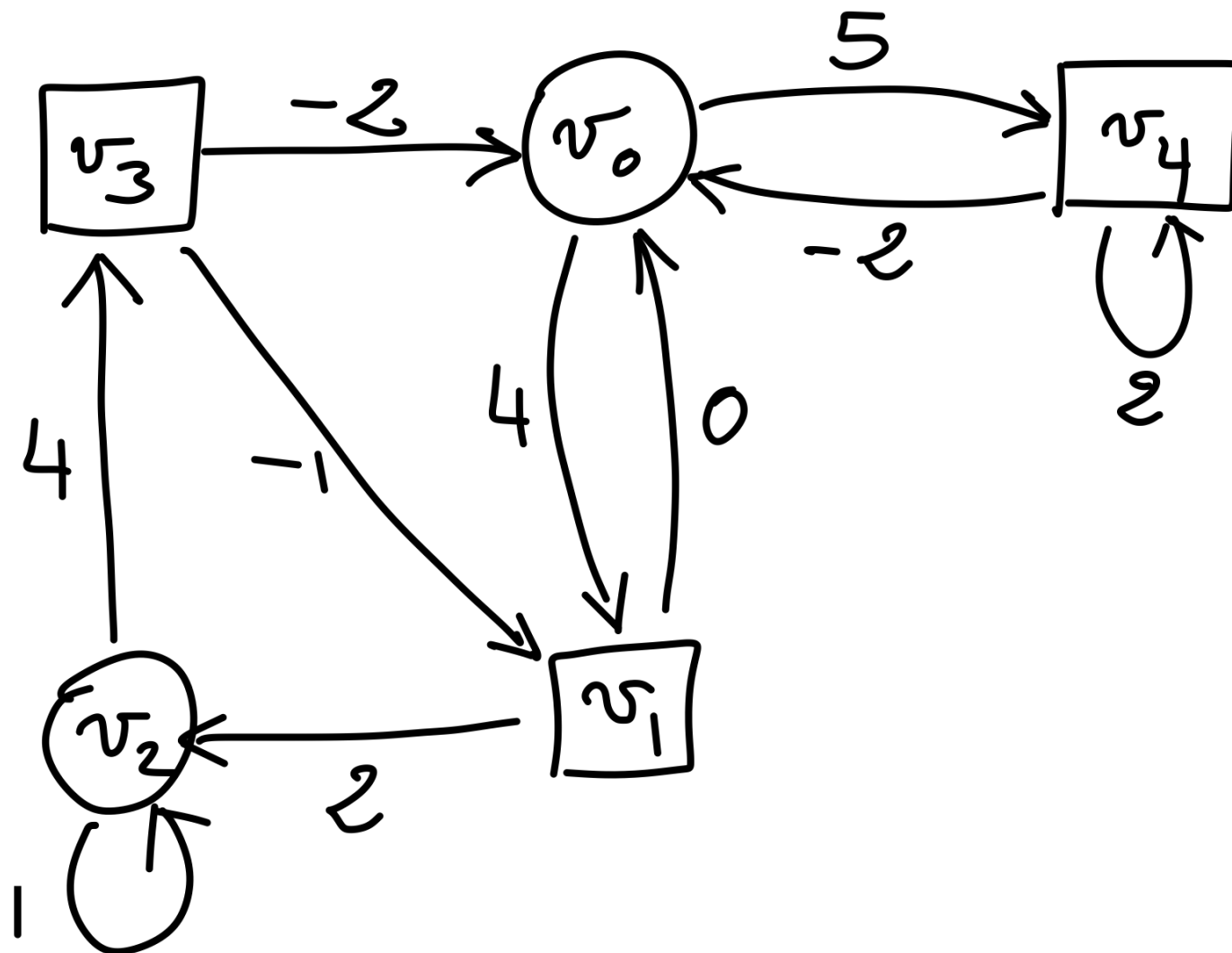
$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{MP}(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v)$$

$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{MP}(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v)$$

3. The winner, with respect to a fixed threshold, can be decided in  $\text{NP} \cap \text{co-NP}$ .



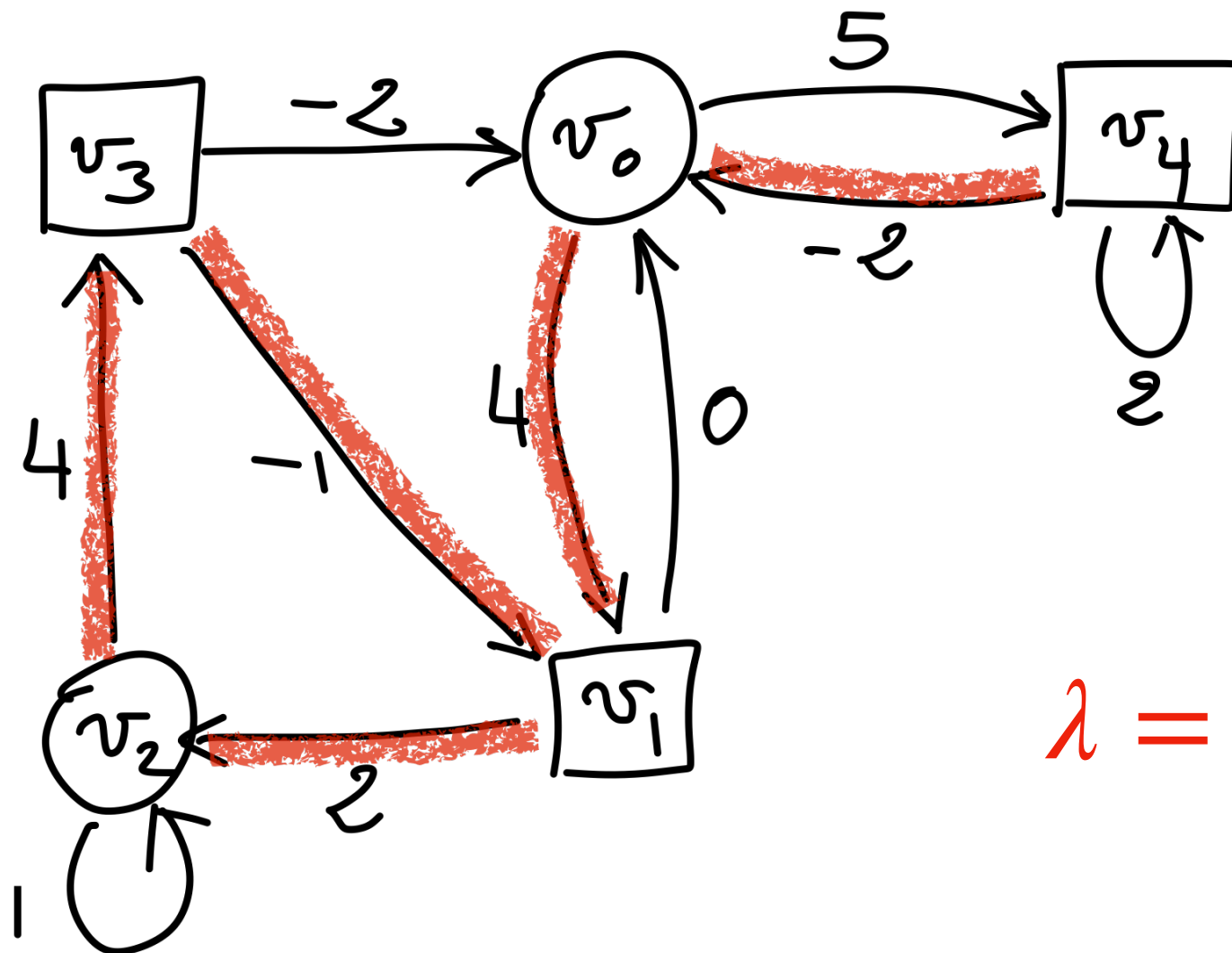
# Discounted-payoff games



**Be good soon enough:**  $(1 - \lambda) \sum_{i=0}^{\infty} \lambda^i r_i$   
 $0 < \lambda < 1$

When  $\lambda \rightarrow 0$  only prefixes matter  
 When  $\lambda \rightarrow 1$  DP looks a lot like MP

# Discounted-payoff games



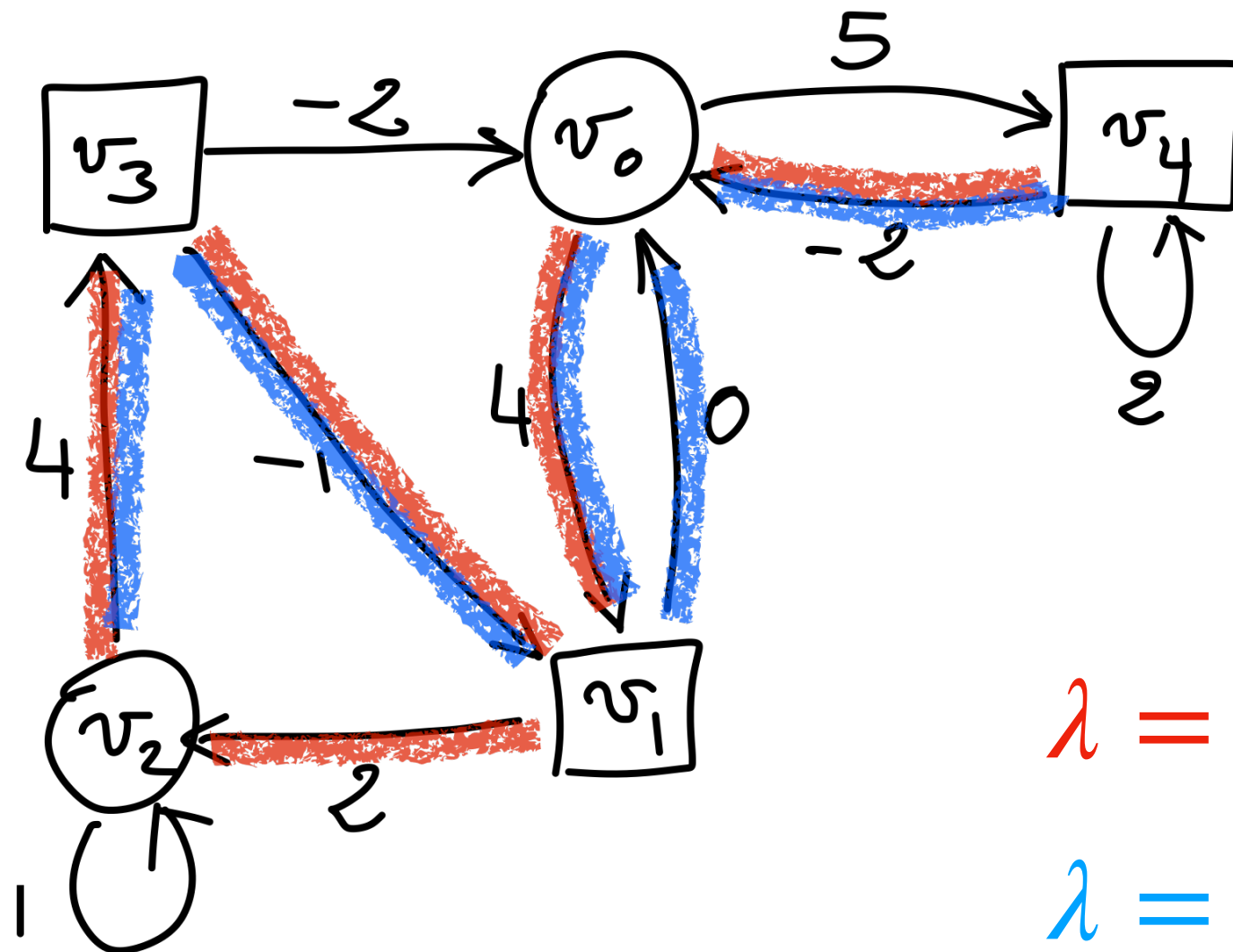
**Be good soon enough:**  $(1 - \lambda) \sum_{i=0}^{\infty} \lambda^i r_i$   
 $0 < \lambda < 1$

When  $\lambda \rightarrow 0$  only prefixes matter  
 When  $\lambda \rightarrow 1$  DP looks a lot like MP

$\lambda = 0.9$

same strategy as for MP

# Discounted-payoff games



**Be good soon enough:**  $(1 - \lambda) \sum_{i=0}^{\infty} \lambda^i r_i$   
 $0 < \lambda < 1$

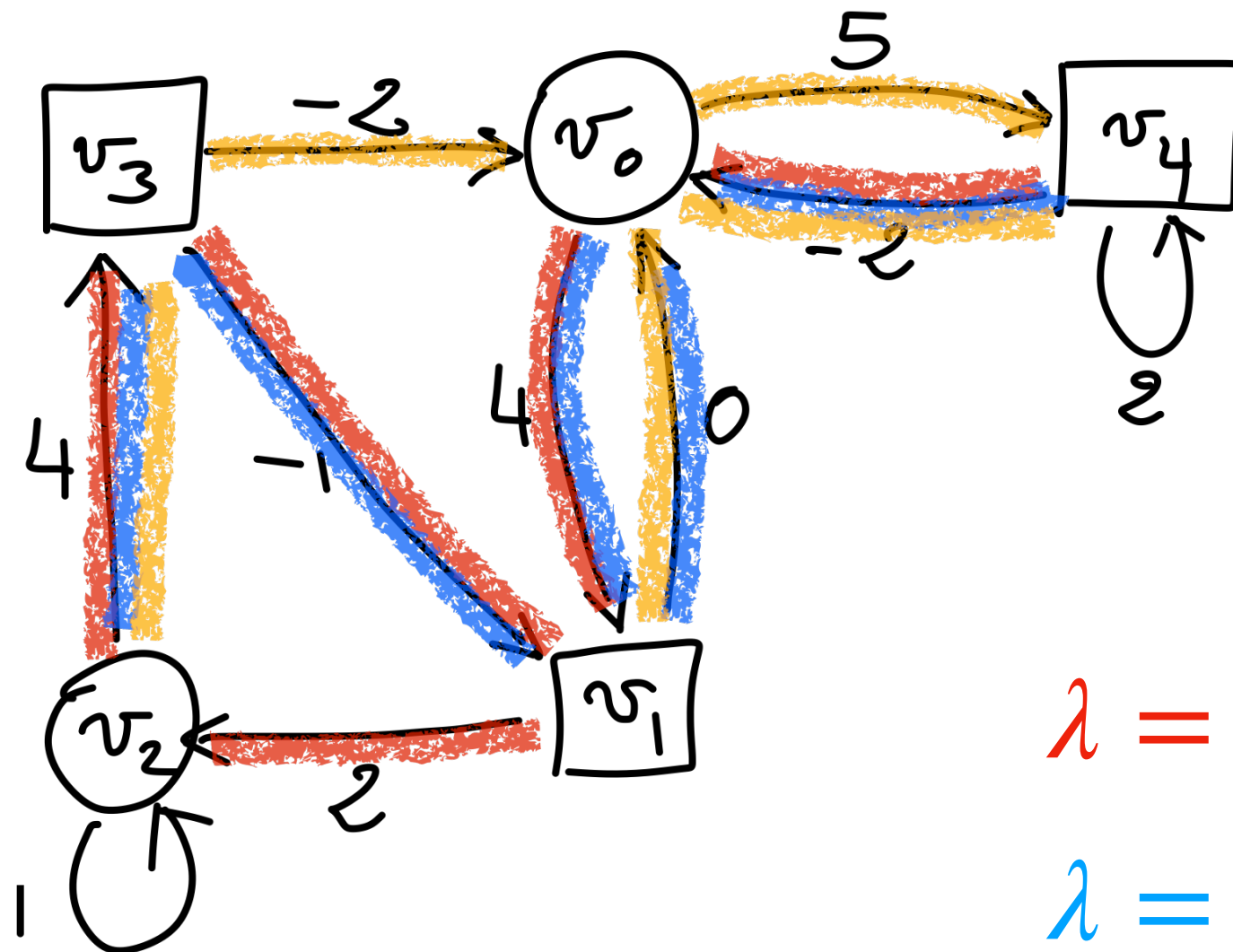
When  $\lambda \rightarrow 0$  only prefixes matter  
 When  $\lambda \rightarrow 1$  DP looks a lot like MP

$\lambda = 0.9$

same strategy as for MP

$\lambda = 0.5$

# Discounted-payoff games



**Be good soon enough:**  $(1 - \lambda) \sum_{i=0}^{\infty} \lambda^i r_i$   
 $0 < \lambda < 1$

When  $\lambda \rightarrow 0$  only prefixes matter  
 When  $\lambda \rightarrow 1$  DP looks a lot like MP

$$\lambda = 0.9$$

*same strategy as for MP*

$$\lambda = 0.5$$

$$\lambda = 0.1$$

# Memoryless determinacy

## Theorem (Zwick-Paterson 1997)

1. Discounted-payoff games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$
2. Both players have *optimal* memoryless strategies:  
$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{DP}_\lambda(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v)$$
$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{DP}_\lambda(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v)$$
3. The winner, with respect to a fixed threshold, can be decided in  $\text{NP} \cap \text{co-NP}$ .

# Proof: finite horizon

$$F(x)_v = \begin{cases} \max_{(v,v') \in E} [(1 - \lambda)r(v, v') + \lambda x_{v'}] & \text{if } v \in V_O \\ \min_{(v,v') \in E} [(1 - \lambda)r(v, v') + \lambda x_{v'}] & \text{if } v \in V_\square \end{cases}$$

$$F: \mathbf{R}^V \rightarrow \mathbf{R}^V \quad \text{contraction mapping}$$

By Banach theorem, unique fixed point

$$F(x^*) = x^*$$

$$x^* = \lim_{n \rightarrow \infty} F^n(\mathbf{0})$$

following strategies dictated by  $F(x^*) = x^*$

$$\text{Val}_O(v) \leq x_v^* \leq \text{Val}_\square(v)$$

always true

$$\text{Val}_\square(v) \leq \text{Val}_O(v)$$

$$x^* = \text{Val}$$



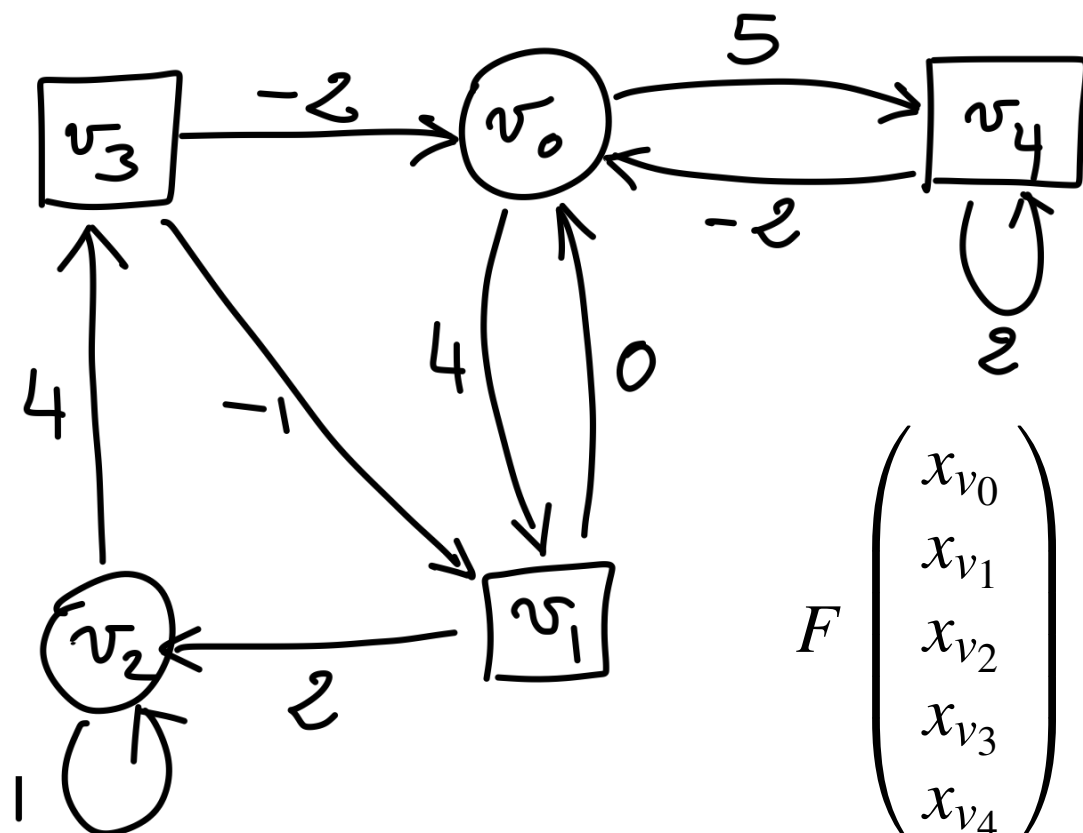
# Memoryless determinacy

## Theorem (Zwick-Paterson 1997)

1. Discounted-payoff games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$
2. Both players have *optimal* memoryless strategies:  

$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{DP}_\lambda(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v)$$

$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{DP}_\lambda(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v)$$
3. The winner, with respect to a fixed threshold, can be decided in  $\text{NP} \cap \text{co-NP}$ .



$$F \begin{pmatrix} x_{v_0} \\ x_{v_1} \\ x_{v_2} \\ x_{v_3} \\ x_{v_4} \end{pmatrix} = \begin{pmatrix} \max(4(1-\lambda) + \lambda x_{v_1}, (1-\lambda)5 + \lambda x_{v_4}) \\ \min(\lambda x_{v_0}, 2(1-\lambda) + \lambda x_{v_2}) \\ \max((1-\lambda) + \lambda x_{v_2}, 4(1-\lambda) + \lambda x_{v_3}) \\ \min(-2(1-\lambda) + \lambda x_{v_0}, -(1-\lambda) + \lambda x_{v_1}) \\ \min(-2(1-\lambda) + \lambda x_{v_0}, 2(1-\lambda) + \lambda x_{v_4}) \end{pmatrix}$$

# How to compute optimal values?

$$F(x)_v = \begin{cases} \max_{(v,v') \in E} [(1 - \lambda)r(v, v') + \lambda x_{v'}] & \text{if } v \in V_O \\ \min_{(v,v') \in E} [(1 - \lambda)r(v, v') + \lambda x_{v'}] & \text{if } v \in V_\square \end{cases}$$

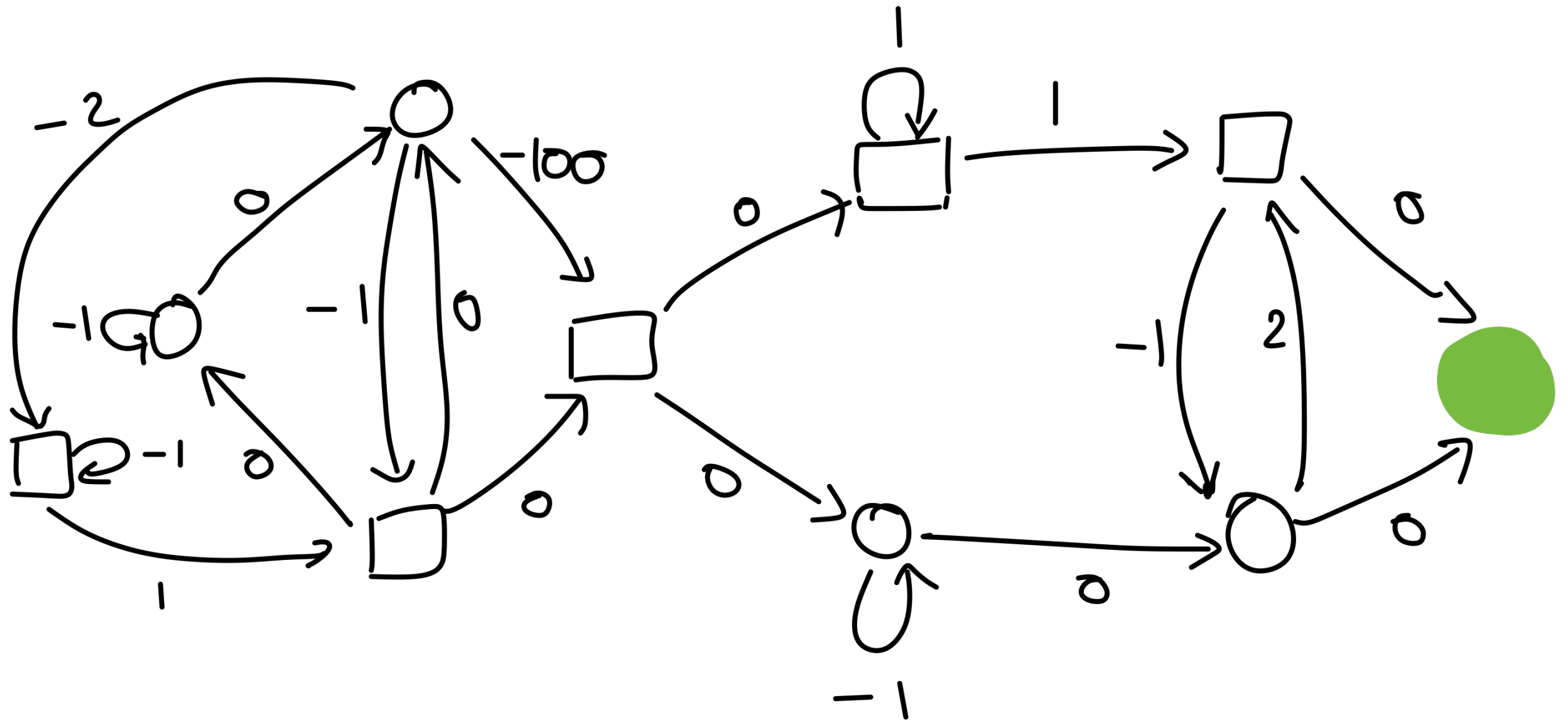
$$x^* = \lim_{n \rightarrow \infty} F^n(\mathbf{0})$$

When to stop the computation, supposing every weight is rational?

1. If  $\lambda = a/b$  is rational, then  $x_v^*$  is rational too, of denominator  $D = b^{O(|V|^2)}$
2. If  $K$  is big enough (*polynomial* in  $|V|$ , *exponential* in  $\lambda$ ), then
$$\|F^K(\mathbf{0}) - \text{Val}\|_\infty \leq 1/2D$$
3. Use a rounding procedure to deduce Val from  $F^K(\mathbf{0})$

**Pseudo-polynomial algorithm**

# Shortest-path games



Player  $\square$  wants to reach the target with the smallest weight

Player  $\bigcirc$  wants to avoid the target, and if not possible, maximise the weight to the target

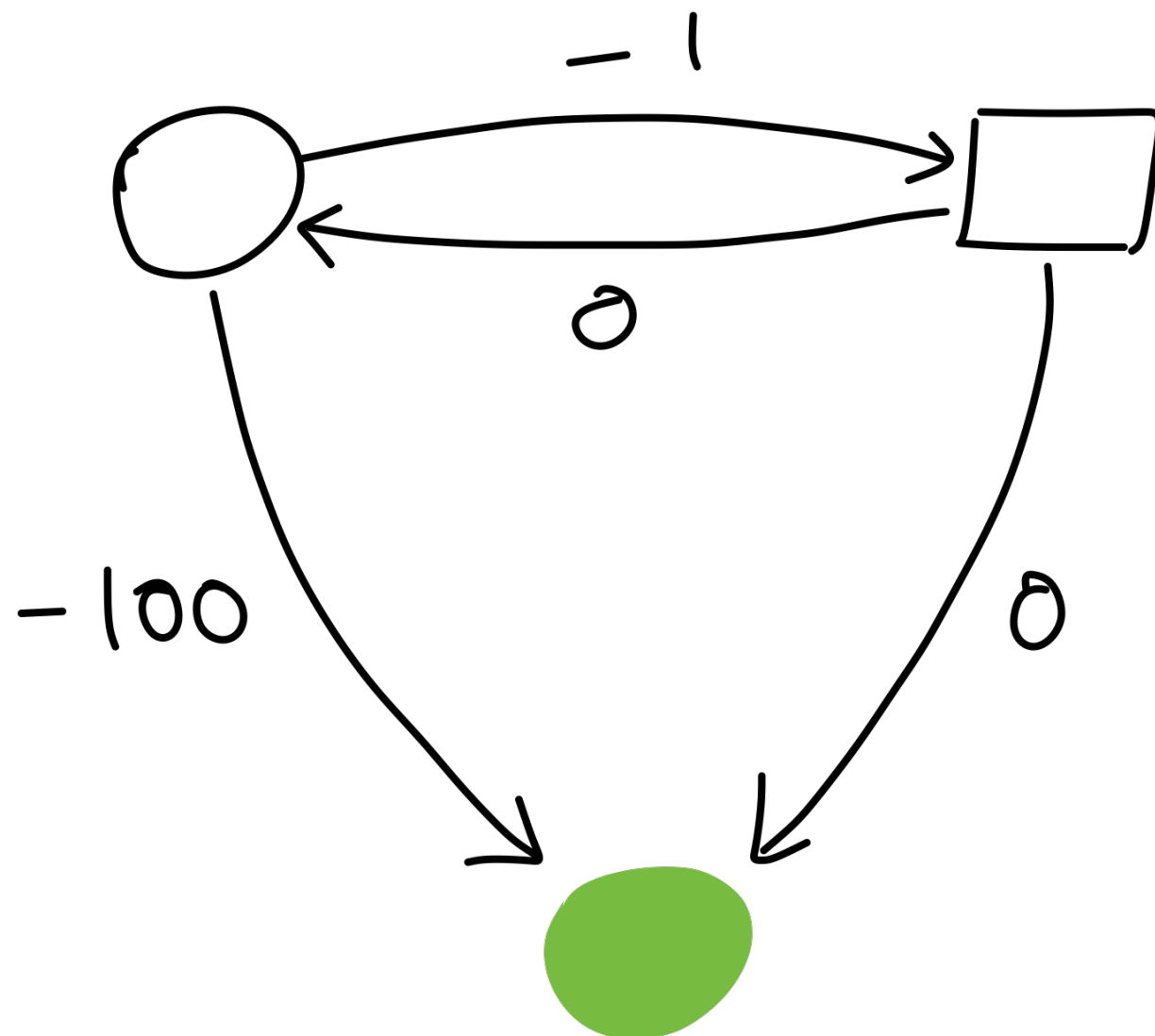
# Non-negative case

## Theorem (Khachiyan *et al* 2008)

1. Shortest-path games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$
2. Both players have *optimal* memoryless strategies:  
$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{DP}_\lambda(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v)$$
$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{DP}_\lambda(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v)$$
3. The winner, with respect to a fixed threshold, can be decided in polynomial time.

Adaptation of Dijkstra's shortest-path algorithm from graphs to games...

# Negative weights



Player  $\square$  needs memory to play optimally!

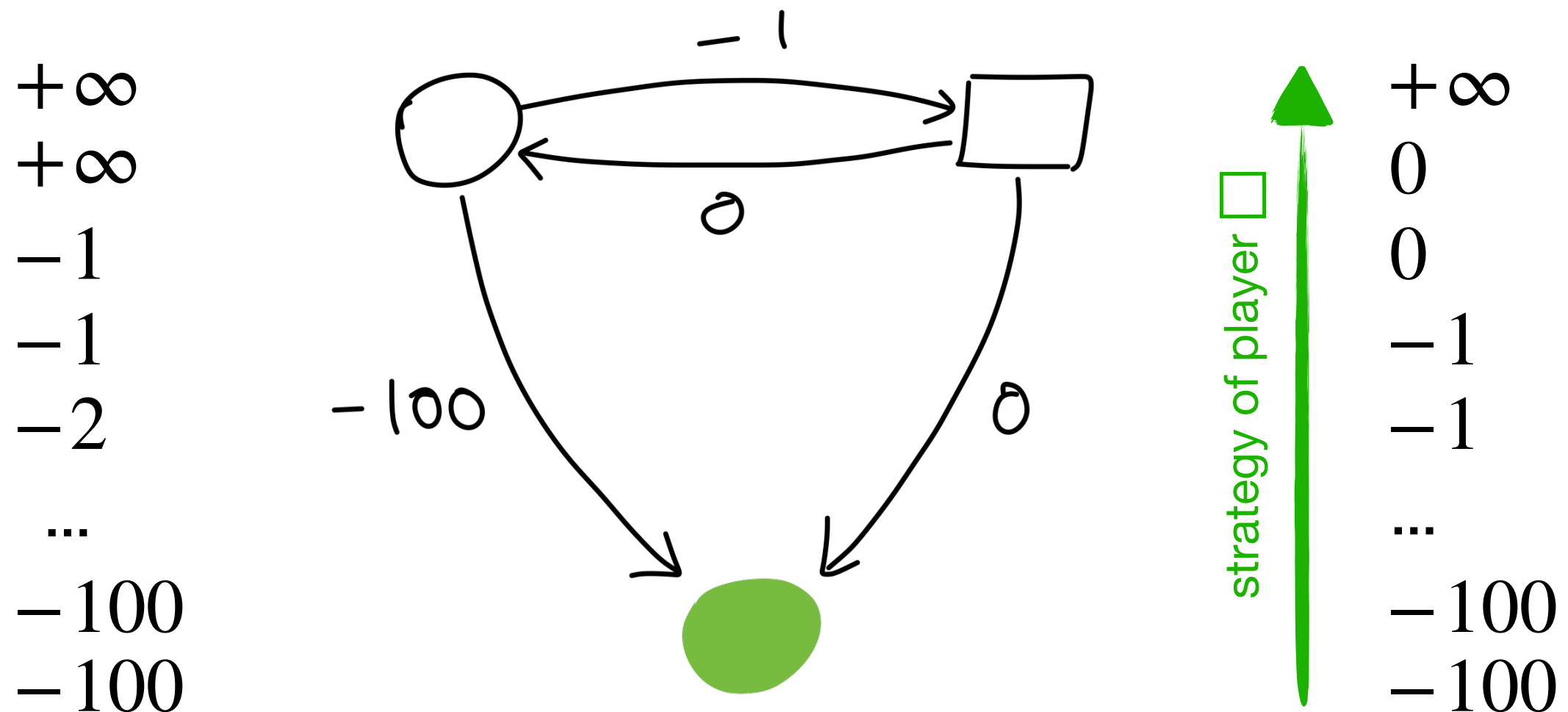
# Non-negative case

## Theorem (Brihaye, Geeraerts, Haddad, Monmege 2015)

1. Shortest-path games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$
2. Both players have *optimal* ~~memoryless~~ strategies:  
$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{DP}_\lambda(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v) \quad \rightarrow \text{memoryless}$$
$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{DP}_\lambda(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v) \quad \rightarrow \text{may require finite memory}$$
3. The winner, with respect to a fixed threshold, can be decided in pseudo-polynomial time.

# Computation of the optimal values

$$F(x)_v = \begin{cases} 0 & \text{if } v \in V_{\text{target}} \\ \max_{(v,v') \in E} [r(v, v') + x_{v'}] & \text{if } v \in V_O \\ \min_{(v,v') \in E} [r(v, v') + x_{v'}] & \text{if } v \in V_{\square} \end{cases}$$



# Non-negative case

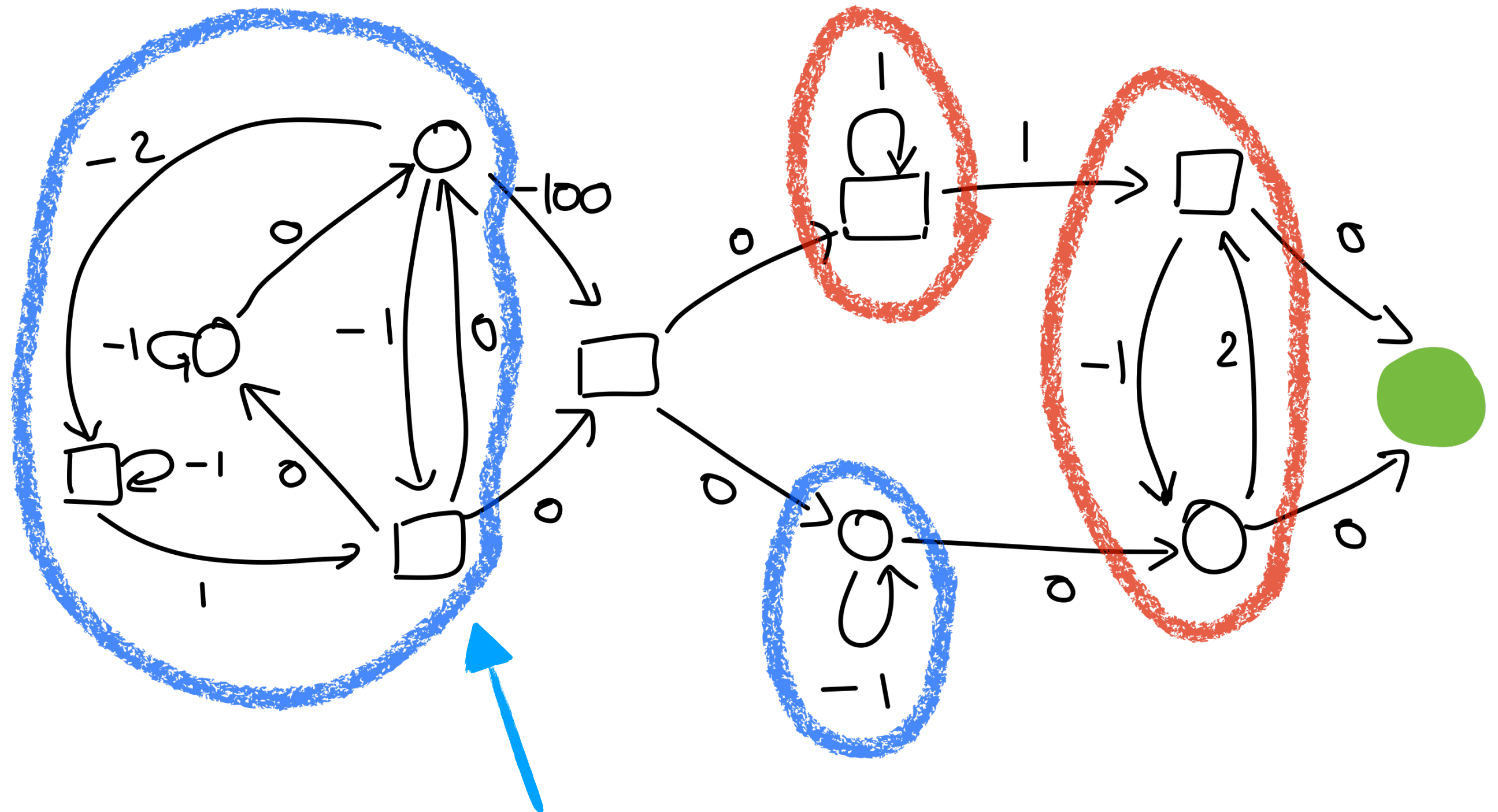
## Theorem (Brihaye, Geeraerts, Haddad, Monmege 2015)

1. Shortest-path games are determined:  $\forall v \quad \text{Val}_O(v) = \text{Val}_\square(v) =: \text{Val}(v)$
2. Both players have *optimal* ~~memoryless~~ strategies:  
$$\exists \sigma_O^* \forall v \quad \inf_{\sigma_\square} \text{DP}_\lambda(\text{play}(v, \sigma_O^*, \sigma_\square)) = \text{Val}(v) \quad \rightarrow \text{memoryless}$$
$$\exists \sigma_\square^* \forall v \quad \sup_{\sigma_O} \text{DP}_\lambda(\text{play}(v, \sigma_O, \sigma_\square^*)) = \text{Val}(v) \quad \rightarrow \text{may require finite memory}$$
3. The winner, with respect to a fixed threshold, can be decided in pseudo-polynomial time.

Polynomial wrt  $|V|$   
Polynomial wrt weights encoded in unary



# Interesting fragment?



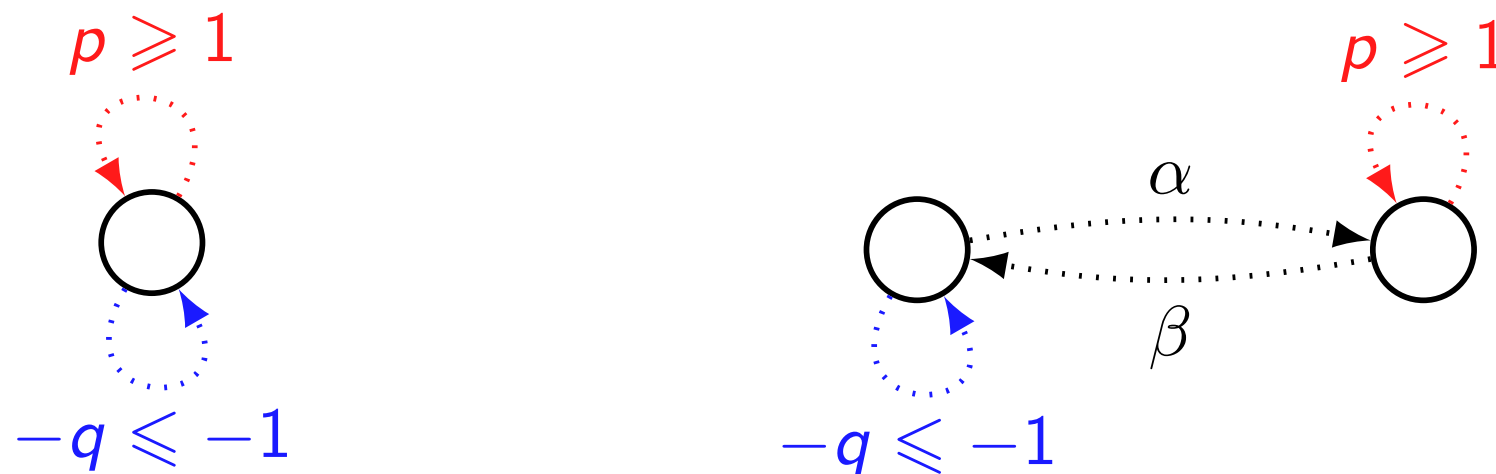
only case where pseudo-polynomial complexity...

# Divergent weighted games

No cycles of weight = 0

## Characterisation (Busatto-Gaston, Monmege, Reynier 2017)

All cycles in an SCC have the same sign.



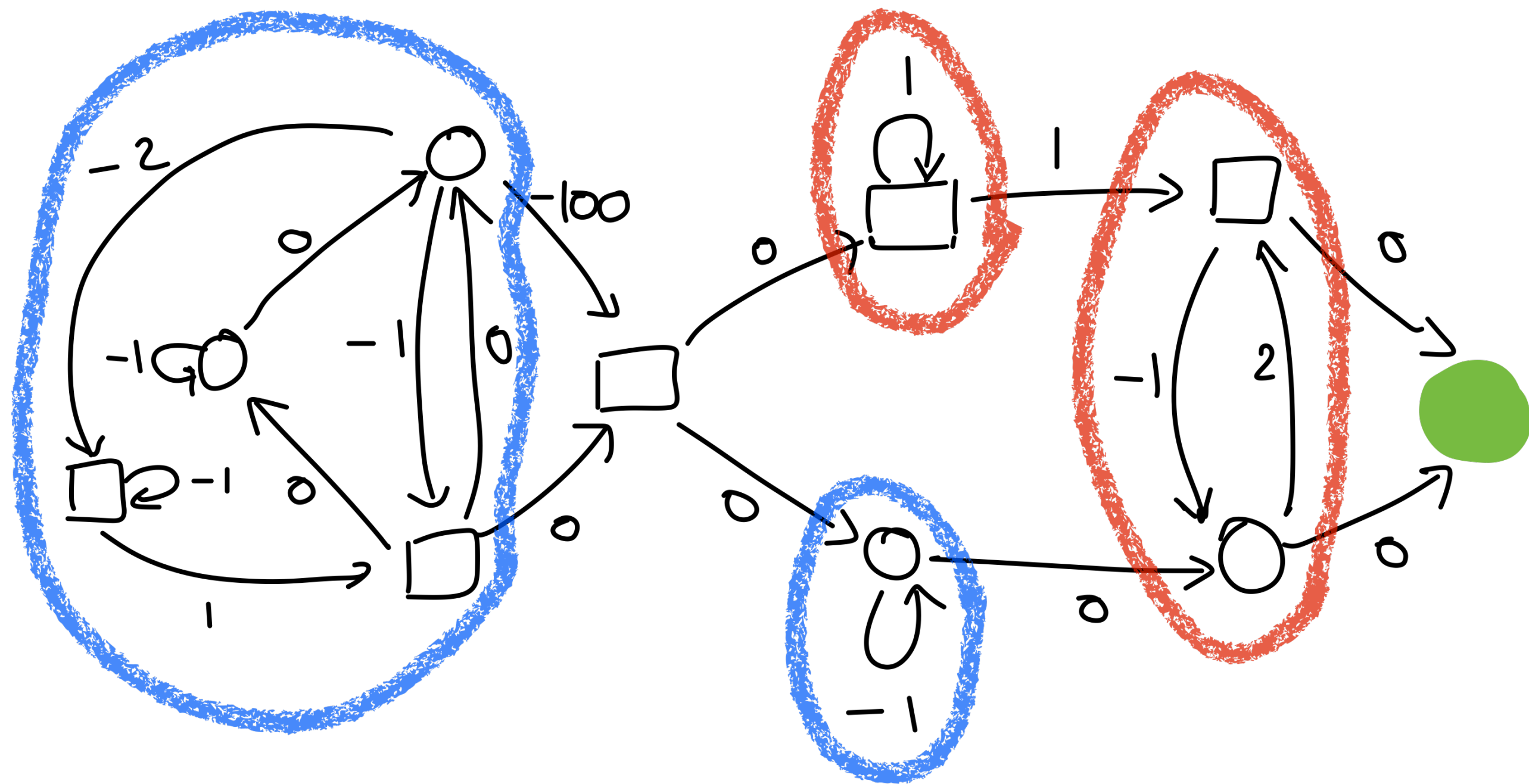
In positive SCCs, value iteration algorithm converges in polynomial time.

In negative SCCs :

1. outside the attractor of Player  $\bigcirc$   $\rightarrow$  value  $-\infty$
2. value iteration algorithm starting from  $-\infty$  (instead of  $+\infty$ ) converges in polynomial time

## Theorem (Busatto-Gaston, Monmege, Reynier 2017)

Optimal values/strategies in divergent weighted games are computable in polynomial time.



Environment  $\parallel$  Controller??  $\models$  Spec

Two-player game

Peak-hour



15 c€/kWh

Offpeak-hour



12 c€/kWh

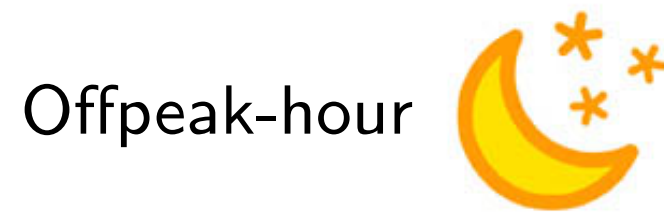
rate: total power  $\times$  15 c€/h

total power  $\times$  12 c€/h



15 c€/kWh

rate: total power  $\times$  15 c€/h



12 c€/kWh

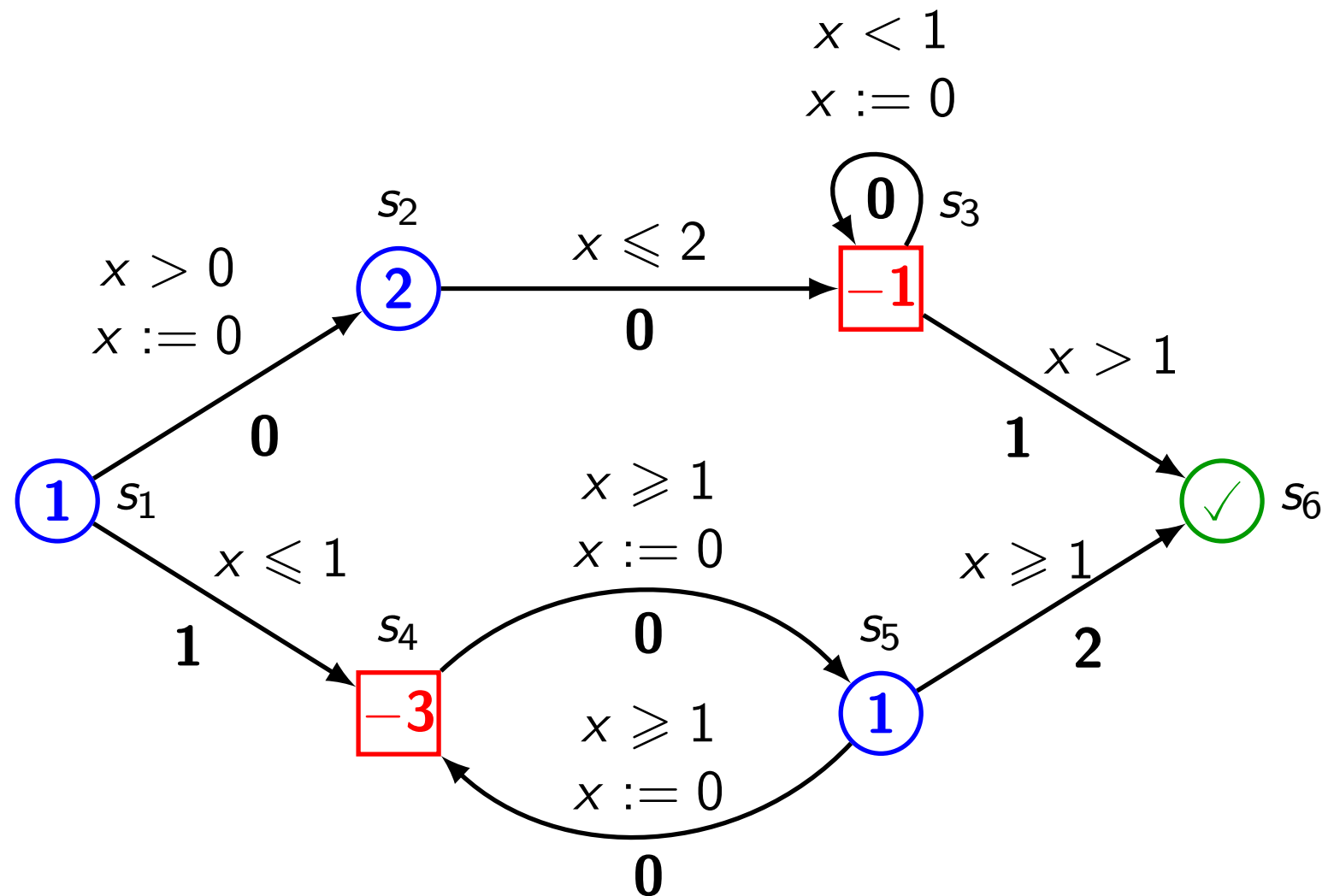
total power  $\times$  12 c€/h



Reselling: 20 c€/kWh

$-0.5 \times 20$  c€/h

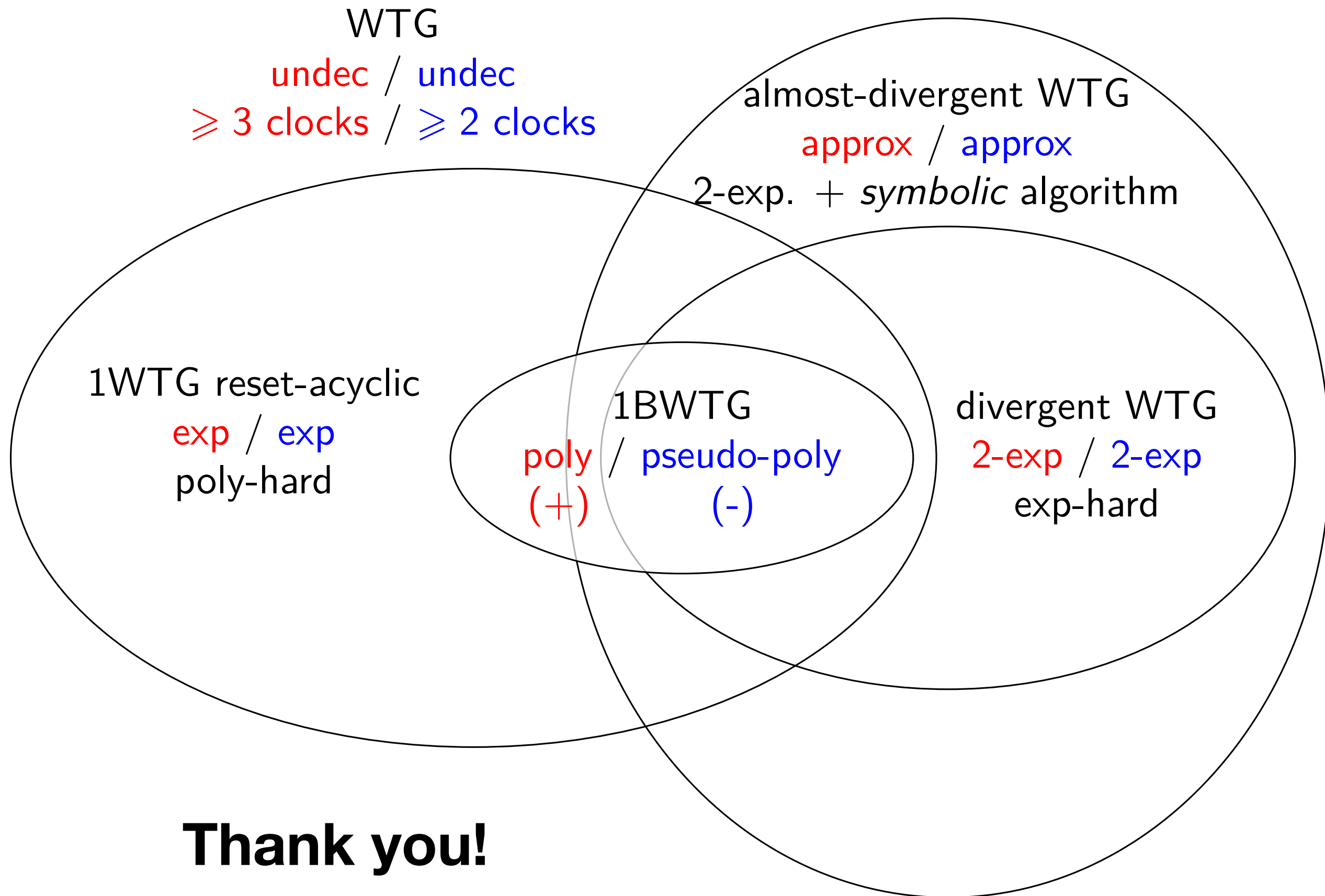
# Weighted timed games



Timed automaton  
with state partition between  
2 players  
+ reachability objective  
+ linear rates on states  
+ discrete weights on  
transitions

$$\begin{aligned}
 (s_1, 0) &\xrightarrow[1 \times 0.4 + 1]{0.4, \searrow} (s_4, 0.4) \xrightarrow[-3 \times 0.6 + 0]{0.6, \rightarrow} (s_5, 0) \xrightarrow[+1 \times 1.5 + 0]{1.5, \leftarrow} (s_4, 0) \xrightarrow[-3 \times 1.1 + 0]{1.1, \rightarrow} (s_5, 0) \xrightarrow[+1 \times 2 + 2]{2, \nearrow} (s_6, 2) \\
 &= 1.8
 \end{aligned}$$

$$\begin{aligned}
 (s_1, 0) &\xrightarrow[1 \times 0.2 + 0]{0.2, \nearrow} (s_2, 0) \xrightarrow[+2 \times 0.9 + 0]{0.9, \rightarrow} (s_3, 0.9) \xrightarrow[-1 \times 0.2 + 0]{0.2, \circlearrowleft} (s_3, 0) \xrightarrow[-1 \times 0.9 + 0]{0.9, \circlearrowleft} (s_3, 0) \dots \\
 &= +\infty
 \end{aligned}$$



**Thank you!**