

The Selection Monad Transformer

Backward Induction with Mixed Strategies

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Tic-Tac-Toe



If both players play optimally, the game ends in a **draw**

Hence **any first move is an optimal move!**

But what if the opponent is likely to make **mistakes...**

Surely some first moves are better than others

How do we calculate strategies that **maximises the chances of your opponent making a mistake?**

How to do this in a **modular / compositional** way?

Plan

- Strong Monads
- Continuation Monad (folding back procedure)
- Selection Monad (backward induction)
- Selection Monad Transformer
- An Example (Tic-Tac-Toe)

Strong Monads

Strong Monads

A function on types $T: \text{Type} \rightarrow \text{Type}$ is a **strong monad** if we have operations:

$$\eta_X : X \rightarrow TX$$

$$(\cdot)^\dagger : (X \rightarrow TY) \rightarrow TX \rightarrow TY$$

satisfying

$$(\eta_X)^\dagger = \text{id}_{TX}$$

$$f^\dagger \circ \eta_X = f \quad (f: X \rightarrow TY)$$

$$(g^\dagger \circ f)^\dagger = g^\dagger \circ f^\dagger \quad (g: Y \rightarrow TZ)$$

Example 1 (Lists)

$$TX = [X]$$

$$\eta(x) = [x]$$

$$f^\dagger(xs) = [y : x \in xs, y \in fx]$$

$$\begin{aligned} (\eta_X)^\dagger(xs) &= [y : x \in xs, y \in [x]] \\ &= [x : x \in xs] \\ &= [x : x \in xs] \end{aligned}$$

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Example 2 (Distributions)

$$\Delta X = [(\mathbb{Q}, X)]$$

$$\eta(x) = [(1, x)]$$

$$f^\dagger(d) = [(p_1 p_2, y) : (p_1, x) \in d, (p_2, y) \in fx]$$

$$\begin{aligned} (\eta_X)^\dagger(xs) &= [(p, x) : (p, x) \in d] \\ &= d \end{aligned}$$

Strong Monad Product

For any strong monad $T: \text{Type} \rightarrow \text{Type}$ we can define an operation

$$\otimes : TX \times TY \rightarrow T(X \times Y)$$

which we can iterate to obtain

$$\bigotimes_i : \prod_i (TX_i) \rightarrow T(\prod_i X)$$

For some strong monads even the countable iteration is well defined

In game theory applications, TX_i captures the “local” strategy at round i and the product operation is used to compose simpler strategies into more complex ones

Continuation Monad

Continuation Monad

For any type R the following type function is a strong monad (**continuation monad**)

$$K_R X = (X \rightarrow R) \rightarrow R$$

with the mappings:

$$\begin{array}{ll} \eta : X \rightarrow K_R X & (\cdot)^\dagger : (X \rightarrow K_R Y) \rightarrow K_R X \rightarrow K_R Y \\ \eta(x) = \lambda \kappa^{X \rightarrow R} . \kappa(x) & f^\dagger(\phi) = \lambda \kappa^{Y \rightarrow R} . \phi(\lambda x^X . (fx)(\kappa)) \end{array}$$

A program $p : X$ in a context $E[p] : R$ views $\lambda x . E[x] : X \rightarrow R$ as its **continuation**

In proof theory the continuation monad is related to double negation translations

In game theory it corresponding to the “folding back procedure”

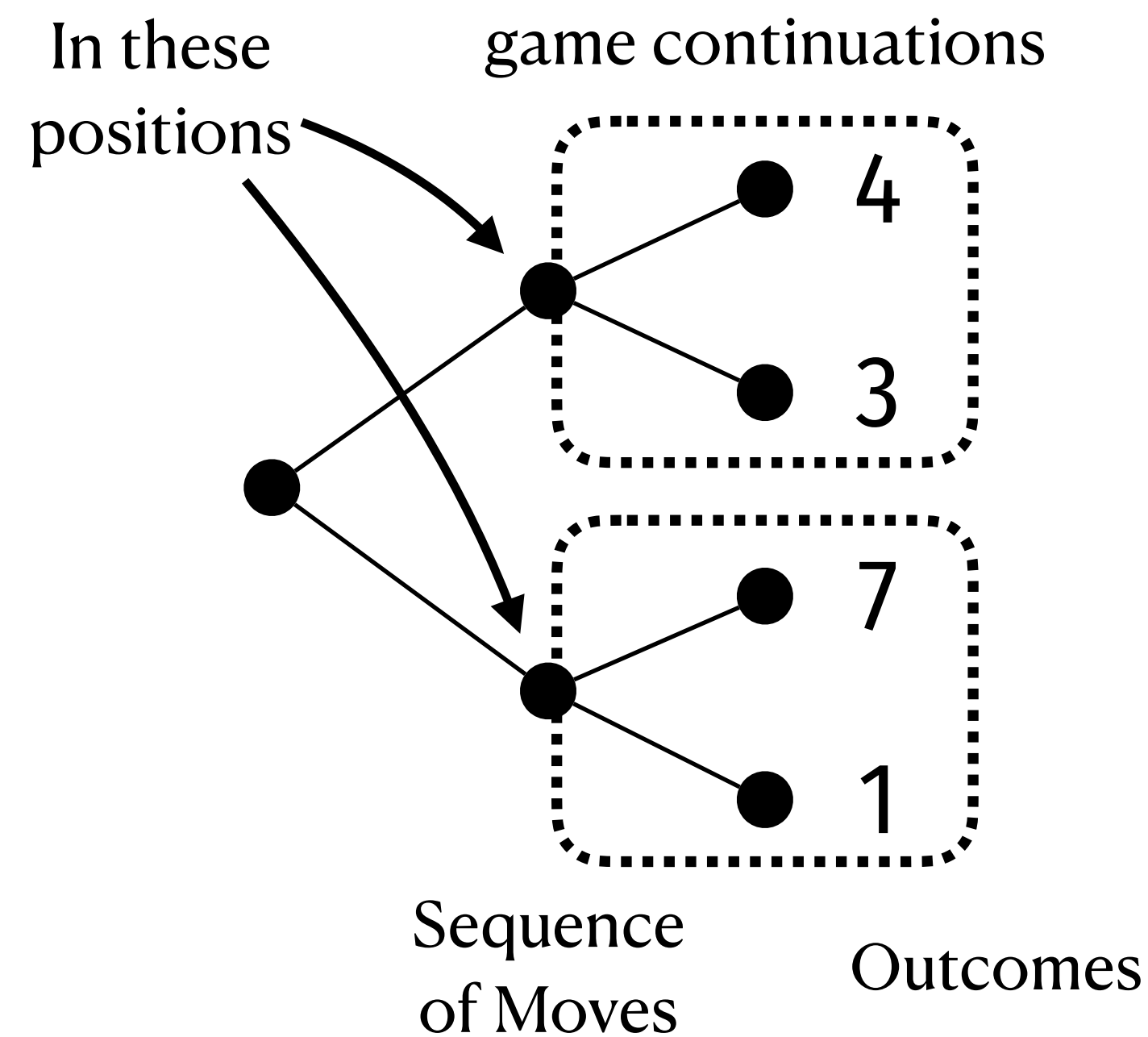
Folding Back Procedure

Given a game in extensive form (tree), and an aggregation function

$$\phi : (X \rightarrow R) \rightarrow R$$

we can “fold back” the game. For instance, suppose our aggregation function is

$$\max : (X \rightarrow \mathbb{R}) \rightarrow \mathbb{R}$$



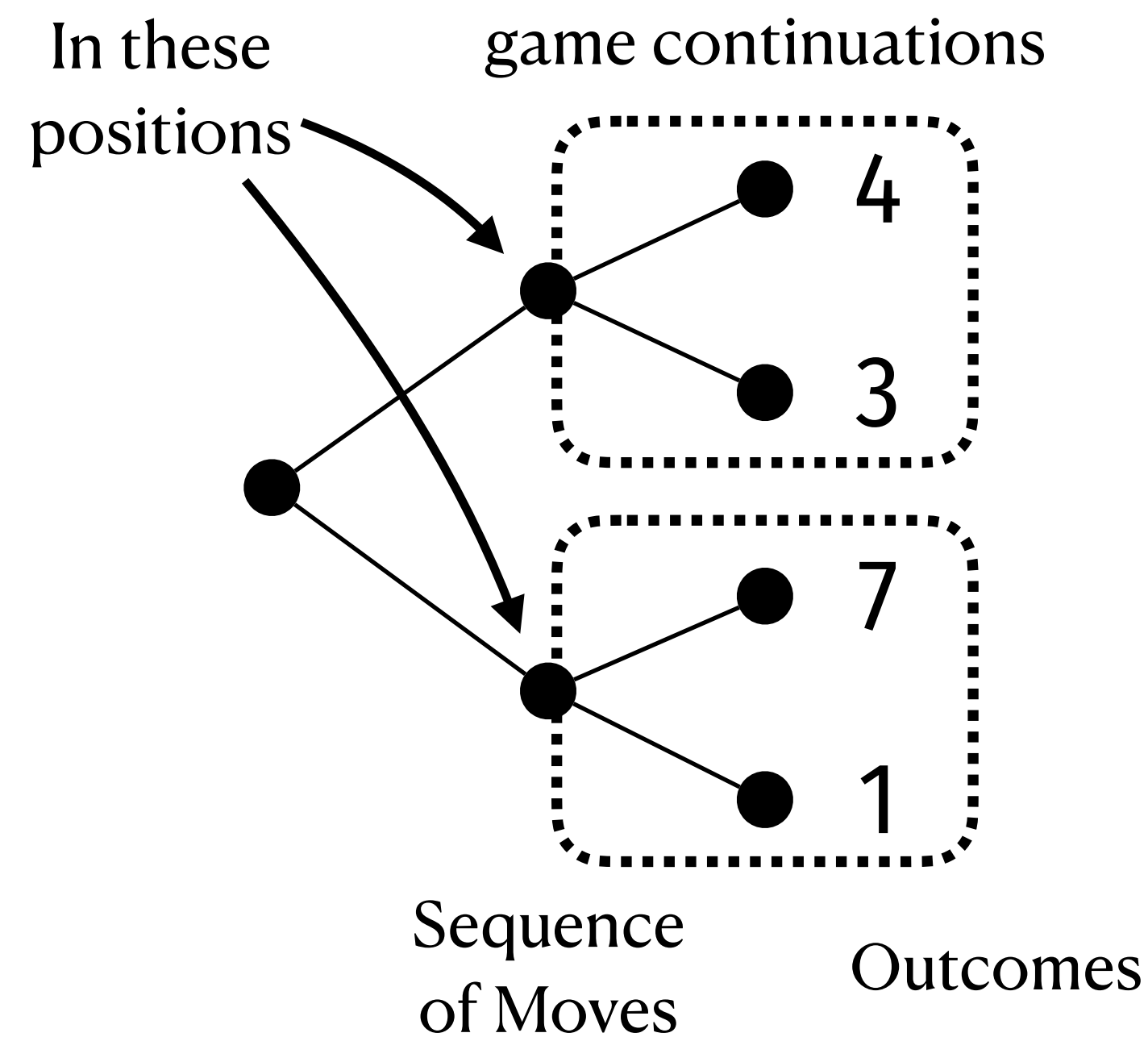
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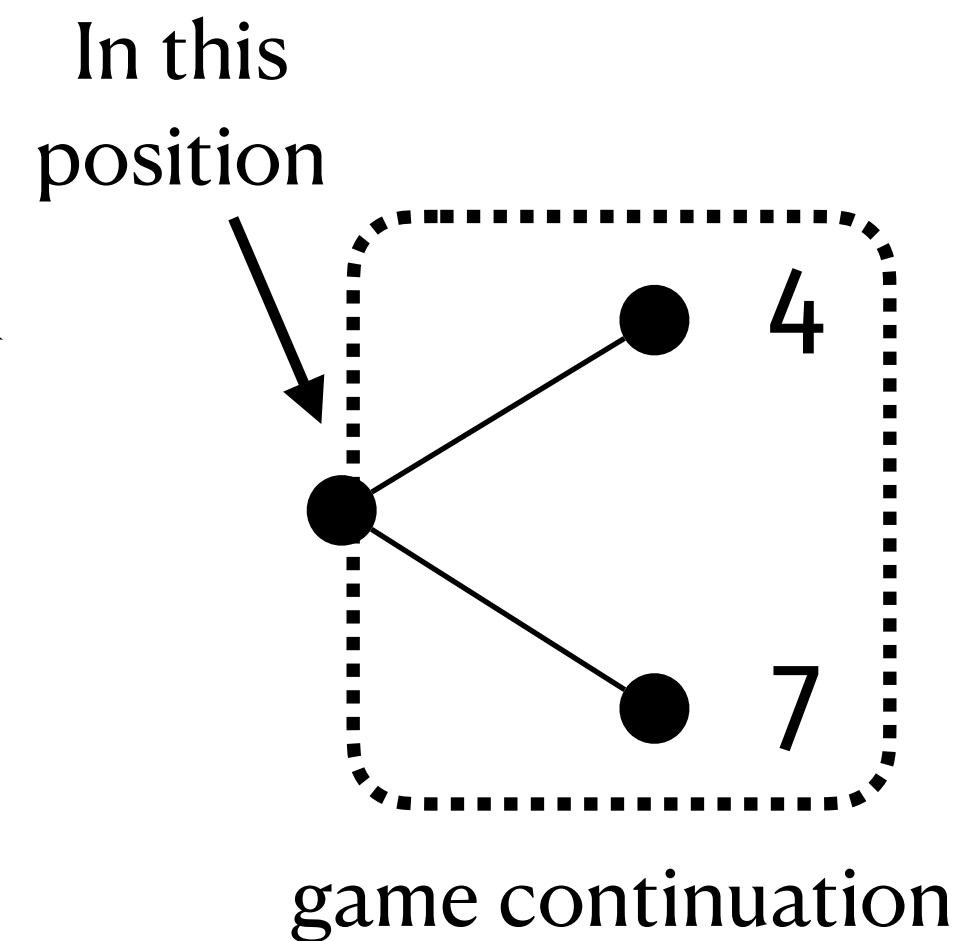
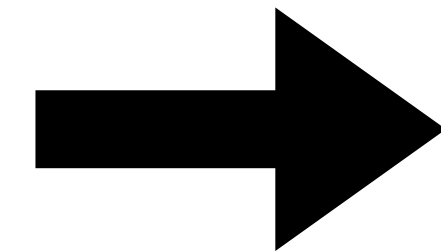
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fold back

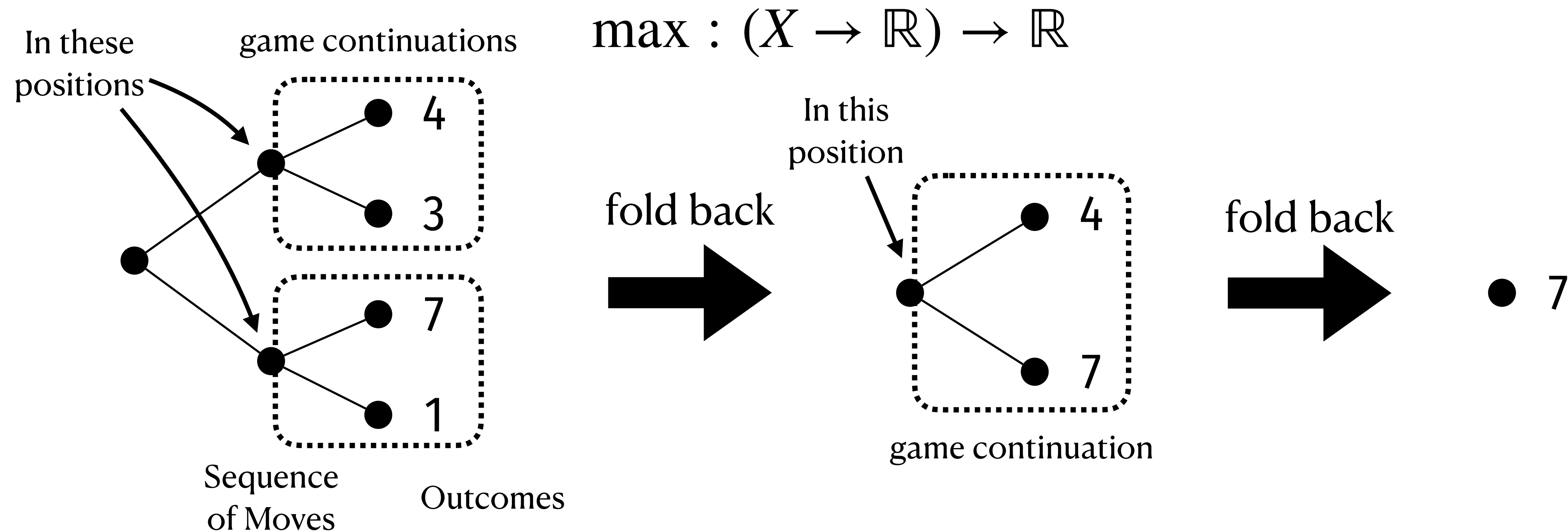


Folding Back Procedure

Given a game in extensive form (tree), and an aggregation function

$$\phi : (X \rightarrow R) \rightarrow R$$

we can “fold back” the game. For instance, suppose our aggregation function is



Selection Monad

Selection Monad

For any type R the following type function is a strong monad (**selection monad**)

$$J_R X = (X \rightarrow R) \rightarrow X$$

with the mappings:

$$\eta : X \rightarrow J_R X$$

$$\eta(x) = \lambda \kappa^{X \rightarrow R} . x$$

$$(\cdot)^\dagger : J_R X \rightarrow (X \rightarrow J_R Y) \rightarrow J_R Y$$

$$f^\dagger(\varepsilon) = \lambda \kappa^{Y \rightarrow R} . f(a(\kappa))(\kappa)$$

where $a(\kappa) = \varepsilon(\lambda x . \kappa(f(x)(\kappa)))$

In proof theory the selection monad is related to the Peirce translation

In game theory it corresponding to “backward induction”
(computing optimal strategies in sequential games)

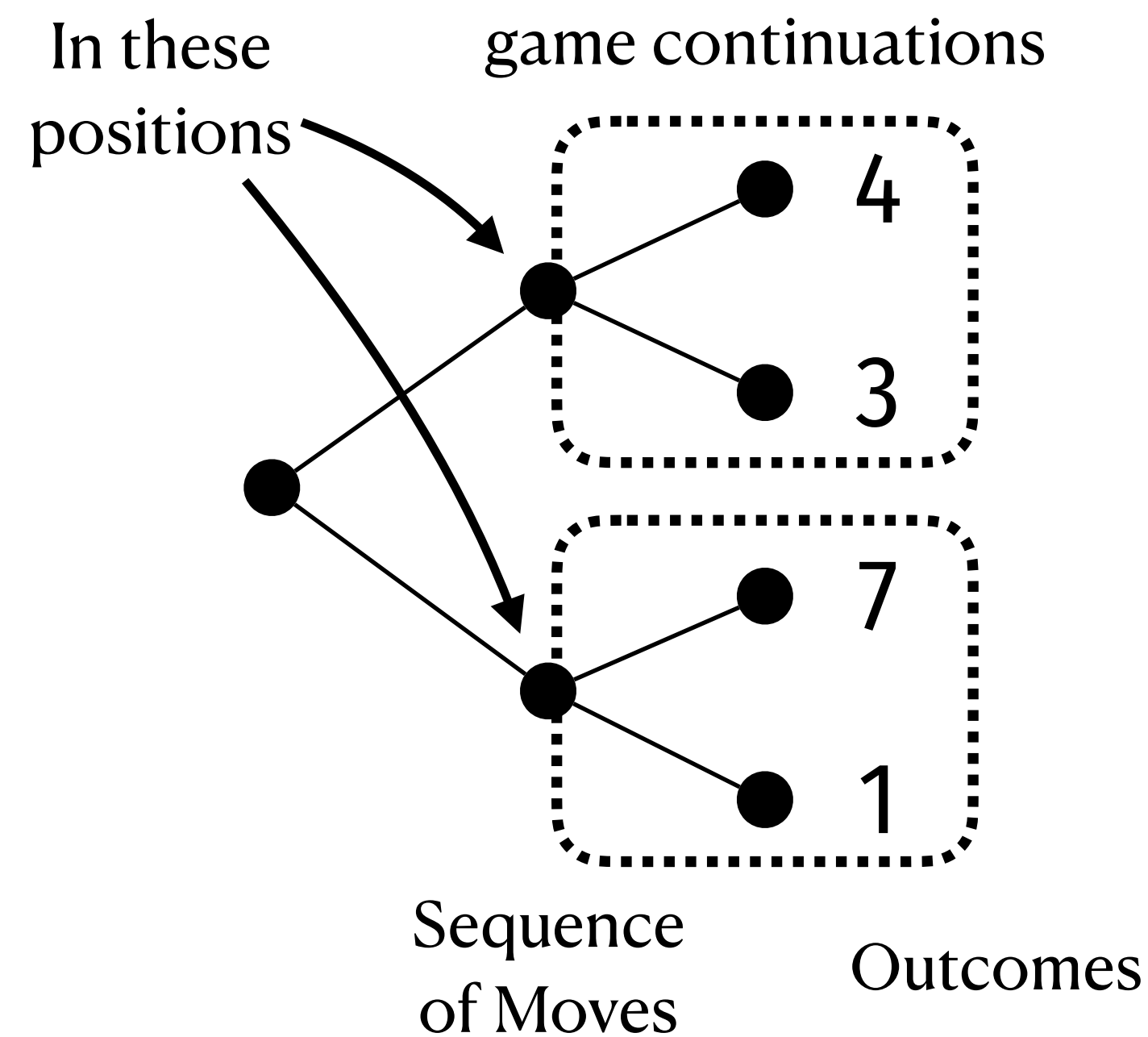
Backward Induction

Given a game in extensive form (tree), and a selection function

$$\varepsilon: (X \rightarrow R) \rightarrow X$$

we can calculate optimal plays. For instance, suppose our selection function is

$$\operatorname{argmax}: (X \rightarrow \mathbb{R}) \rightarrow X$$



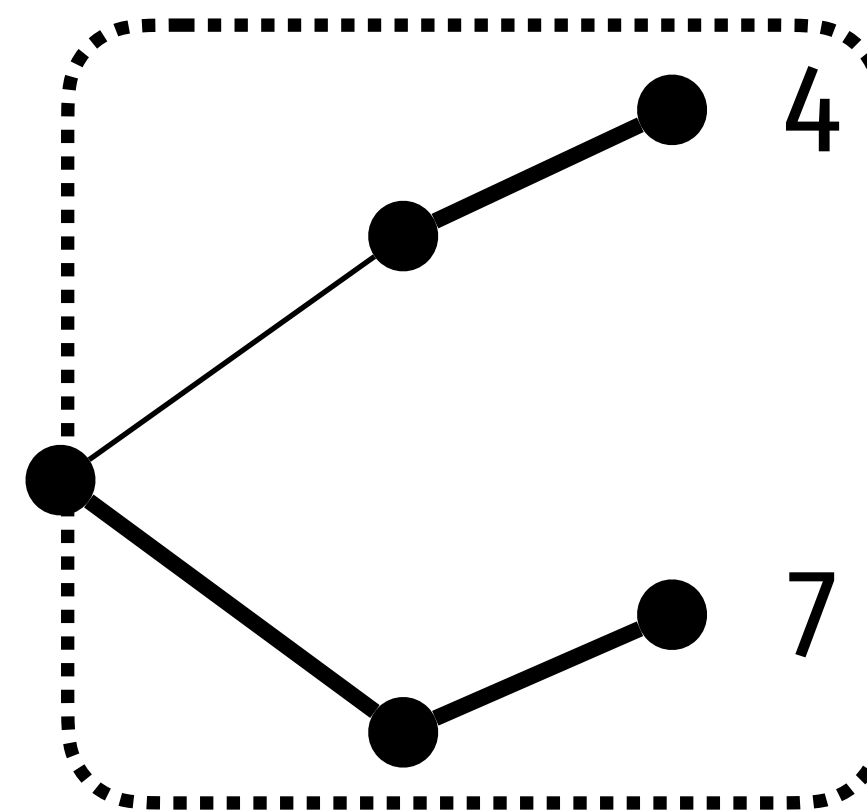
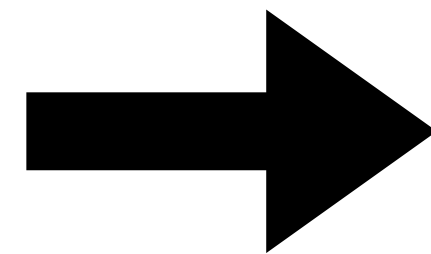
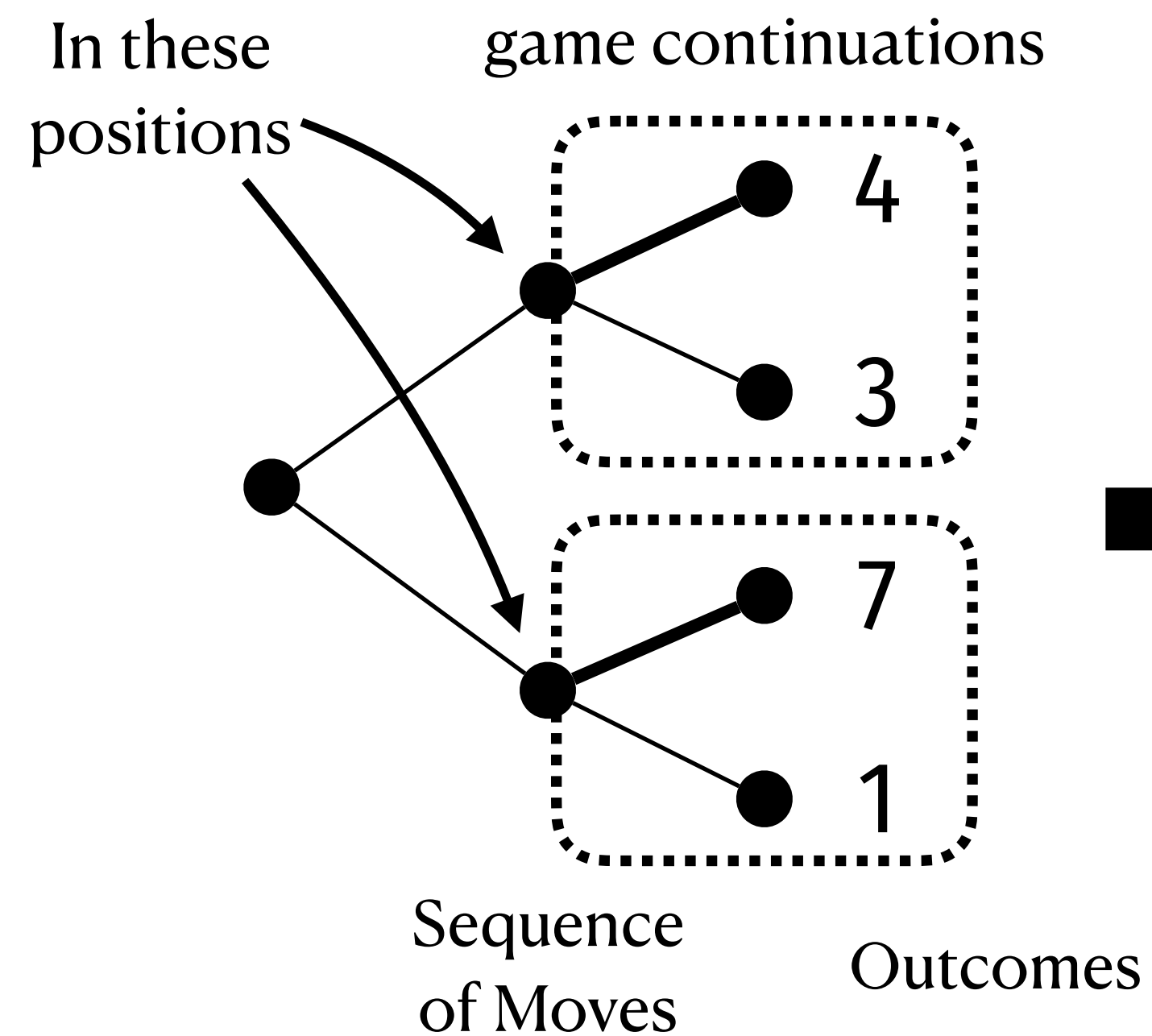
Backward Induction

Given a game in extensive form (tree), and a selection function

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we can calculate optimal plays. For instance, suppose our selection function is

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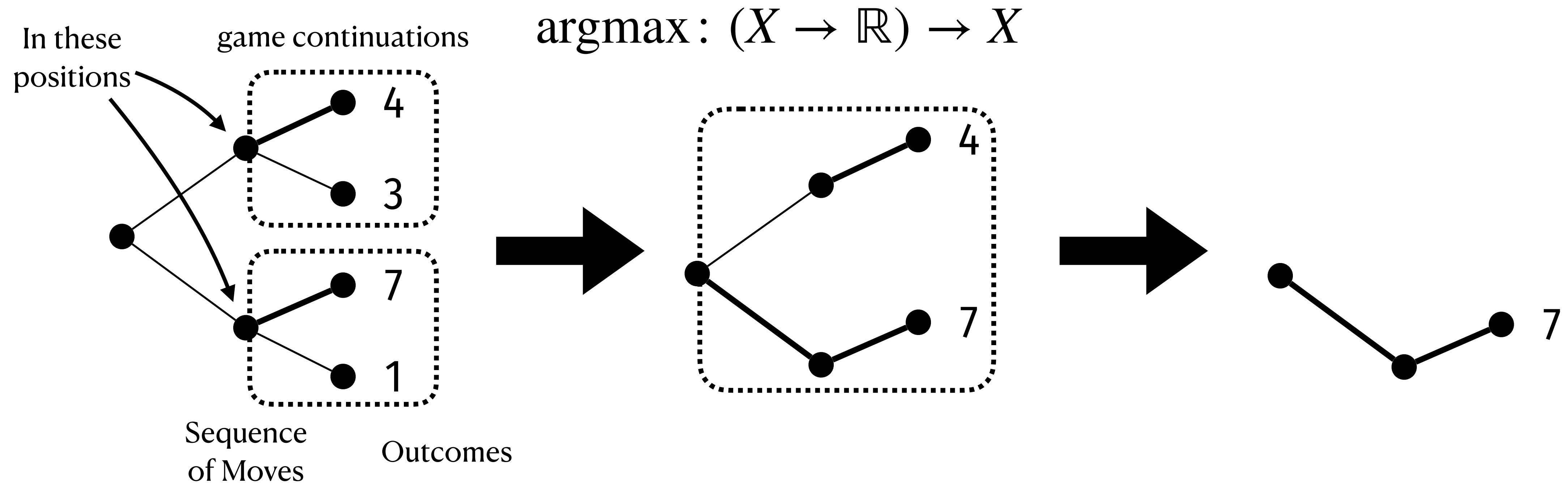


Backward Induction

Given a game in extensive form (tree), and a selection function

$$\varepsilon: (X \rightarrow R) \rightarrow X$$

we can calculate optimal plays. For instance, suppose our selection function is



Selection Monad Transformer

Selection Monad Transformer

For any strong monad M and type R the following is also a strong monad

$$J_R^M X = (X \rightarrow MR) \rightarrow MX$$

Non-deterministic players

$$J_R^{\mathcal{P}} X = \underbrace{(X \rightarrow \mathcal{P}R)}_{\text{For each move we have a set of possible outcomes}} \rightarrow \mathcal{P}X$$

For each move
we have a set
of possible outcomes

choose a
set of
move

Stochastic players

$$J_R^{\Delta} X = \underbrace{(X \rightarrow \Delta R)}_{\text{For each move we have a distribution over outcomes}} \rightarrow \Delta X$$

For each move
we have a distribution
over outcomes

choose a
distribution of
moves

Haskell

```
data J r m x = J {selection :: (x -> m r) -> m x}
```

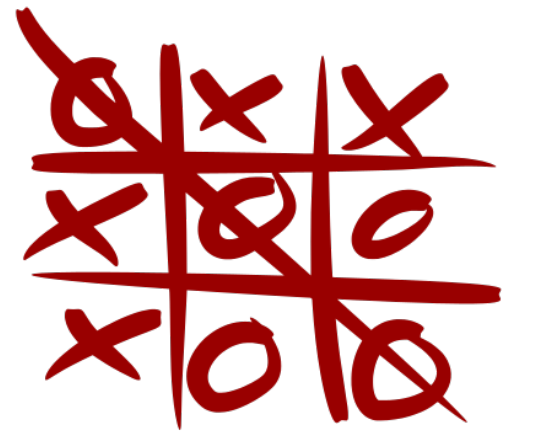
```
instance (Monad m) => Monad (J r m) where  
    return = pure  
    e >>= f = muJ . (fmap f) $ e
```

```
hsequence :: Monad m => [[x] -> m x] -> m [x]  
hsequence [] = return []  
hsequence (xm:xms) = do  
    x <- xm []  
    xs <- hsequence [ \ys -> ym(x:ys) | ym <- xms ]  
    return (x : xs)
```

Tic-Tac-Toe



Tic-Tac-Toe



If both players play optimally, the game ends in a **draw**

Standard backward induction then says that **any first move is an optimal move**

But what if the opponent is likely to make **mistakes**, surely some first moves are better than others

You want to choose a first move that **maximises the chances of your opponent making a mistake**

This can be easily calculated with the **selection monad transformer**

$$J_R^\Delta X = (X \rightarrow \Delta R) \rightarrow \Delta X$$

Demo

Haskell

```
-- TIC-TAC-TOE GAME

-- The board and moves are
--      012      (-1, 1)  (0, 1)  (1, 1)
--      345      or  (-1, 0)  (0, 0)  (1, 0)
--      678      (-1,-1)  (0,-1)  (1,-1)
-- R is the set 3 = {-1,0,1}
```

```
-- Rational maximising player
pR :: [Move] -> J R D Move
pR xs = J (\p -> uniform $ argmax ([0..8] `minus` xs) (probs . p))

-- Rational minimising opponent
oR :: [Move] -> J R D Move
oR xs = J (\p -> uniform $ argmin ([0..8] `minus` xs) (probs . p))

-- Irrational opponent
oI :: [Move] -> J R D Move
oI xs = J (\p -> uniform ([0..8] `minus` xs))
```

```
players :: [[Move] -> J R D Move]
players = [pR, oI, pR, oI, pR, oI, pR, oI, pR]
```

Thank you for your attention!