

# NRLS: Structural Estimation of Directional Dynamic Games With Multiple Equilibria

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Lecture 16  
DSE2025HKU  
December 13, 2025

# ROAD MAP

1. Solving directional dynamic games (DDGs):
  - ▶ Bertrand pricing and investment game
  - ▶ Solving once: State recursion algorithm
  - ▶ Solving for all MPE: Recursive lexicographical search (RLS) algorithm
2. Structural estimation of DDGs: nested MLE RLS
  - ▶ Is it even feasible computationally?
3. Monte Carlo to compare to existing estimators in dynamic games (two-step CCP, NPL, EPL, MPEC)
  - ▶ One equilibrium in the model and data
  - ▶ Multiplicity of equilibria at true parameter
  - ▶ Multiple equilibria in the data



Iskhakov, Rust and Schjerning, 2016, ReStud



Iskhakov, Rust and Schjerning, 2018, IER



Currently: estimation + Monte Carlo exercises

# Dynamic Bertrand price competition

## Directional stochastic dynamic game

- ▶ Two Bertrand competitors,  $n = 2$ , no entry or exit
- ▶ Discrete time, infinite horizon ( $t = 1, 2, \dots, \infty$ )
- ▶ Firms maximize expected discounted profits
- ▶ Each firm has two choices in each period:
  1. Price for the product — simultaneous
  2. Whether or not to buy the state of the art technology
    - ▶ Simultaneous moves
    - ▶ Alternating moves

## Static Bertrand price competition in each period

- ▶ Continuum of consumers make static purchase decision
- ▶ No switching costs: buy from the lower price supplier
- ▶ Per period profits ( $c_i$  is the marginal cost)

$$r_i(c_1, c_2) = \begin{cases} 0 & \text{if } c_i \geq c_j \\ c_j - c_i & \text{if } c_i < c_j \end{cases}$$

# Cost-reducing investments

## State-of-the-art production cost $c$ process

- ▶ Initial value  $c_0$ , lowest value 0:  $0 \leq c \leq c_0$
- ▶ Discretized with  $n$  points
- ▶ Follows exogenous Markov process and only improves
- ▶ Markov transition probability  $\pi(c_{t+1}|c_t)$   
 $\pi(c_{t+1}|c_t) = 0$  if  $c_{t+1} > c_t$

## State space of the problem

- ▶ State of the game: cost structure  $(c_1, c_2, c)$
- ▶ State space is  $S = (c_1, c_2, c) \subset R^3$ :  $c_1 \geq c$ ,  $c_2 \geq c$
- ▶ Actions are observable
- ▶ Private information EV(1) i.i.d. shocks  $\eta\epsilon_{i,I}$  and  $\eta\epsilon_{i,N}$

## Bellman equations, firm 1, simultaneous moves

$$V_1(c_1, c_2, c, \epsilon_1) = \max [v_1(I, c_1, c_2, c) + \eta\epsilon_1(I), v_1(N, c_1, c_2, c) + \eta\epsilon_1(N)]$$

$$\begin{aligned}v_1(N, c_1, c_2, c) &= r_1(c_1, c_2) + \beta EV_1(c_1, c_2, c, N) \\v_1(I, c_1, c_2, c) &= r_1(c_1, c_2) - K(c) + \beta EV_1(c_1, c_2, c, I)\end{aligned}$$

With extreme value shocks, the investment probability (CCP) is

$$P_1(I|c_1, c_2, c) = \frac{\exp\{v_1(I, c_1, c_2, c)/\eta\}}{\exp\{v_1(I, c_1, c_2, c)/\eta\} + \exp\{v_1(N, c_1, c_2, c)/\eta\}}$$

- ▶ There is a separate Bellman equation for player 2, with “outputs”  $V_2$  and  $P_2$ , where  $P_2(I|c_1, c_2, c)$  is firm 2’s probability of investing in state  $(c_1, c_2, c)$ .

## Bellman equations, firm 1, simultaneous moves

The expected values are given by

$$EV_1(c_1, c_2, c, N) = \int_0^c \left[ P_2(I|c_1, c_2, c) H_1(c_1, c, c') + [1 - P_2(I|c_1, c_2, c)] H_1(c_1, c_2, c') \right] \pi(dc'|c)$$

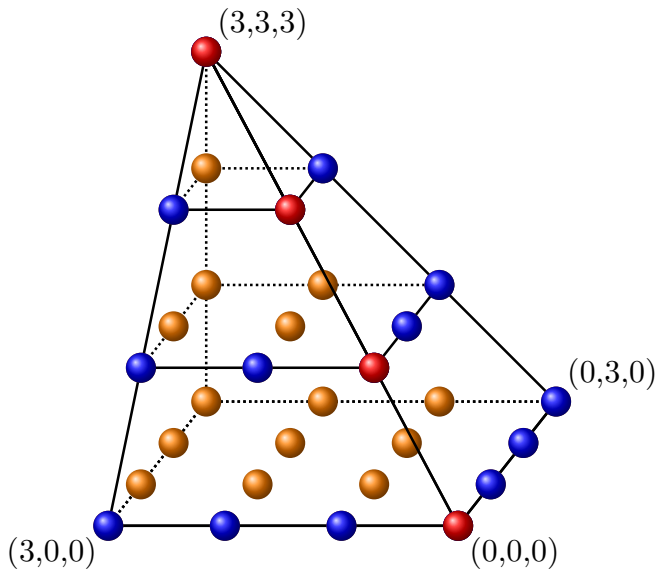
$$EV_1(c_1, c_2, c, I) = \int_0^c \left[ P_2(I|c_1, c_2, c) H_1(c, c, c') + [1 - P_2(I|c_1, c_2, c)] H_1(c, c_2, c') \right] \pi(dc'|c)$$

$$H_1(c_1, c_2, c) = \eta \log \left[ \exp(v_1^N(c_1, c_2, c)/\eta) + \exp(v_1^I(c_1, c_2, c)/\eta) \right].$$

is the “smoothed max” or logsum function

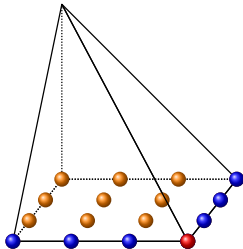
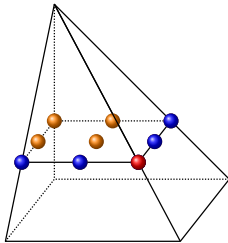
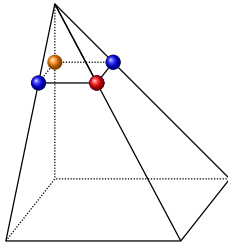
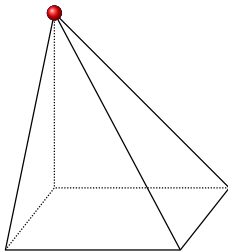
# Discretized state space = a "quarter pyramid"

$$S = \{(c_1, c_2, c) | c_1 \geq c, c_2 \geq c, c \in [0, 3]\}, n = 4$$



# Transitions due to technological progress

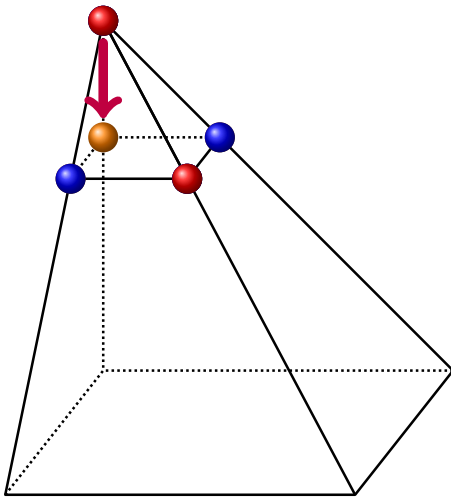
As  $c$  decreases, the game falls through the layers of the pyramid





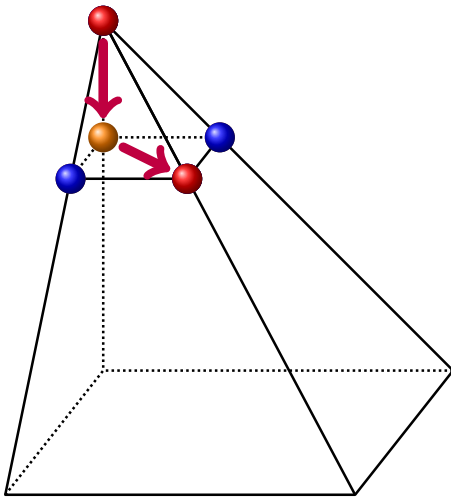
# Game dynamics: example

The game starts at the apex, as some point technology improves



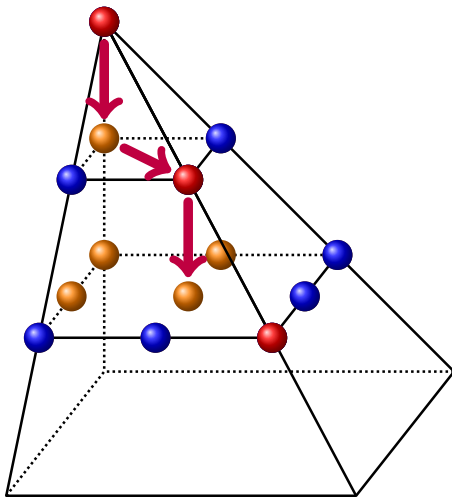
# Game dynamics: example

Both firms buy new technology  $c = 2 \rightsquigarrow (c_1, c_2, c) = (2, 2, 2)$



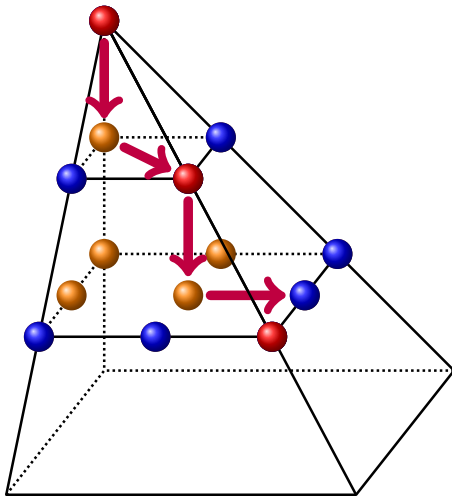
# Game dynamics: example

State-of-the-art technology becomes  $c = 1 \rightsquigarrow (c_1, c_2, c) = (2, 2, 1)$



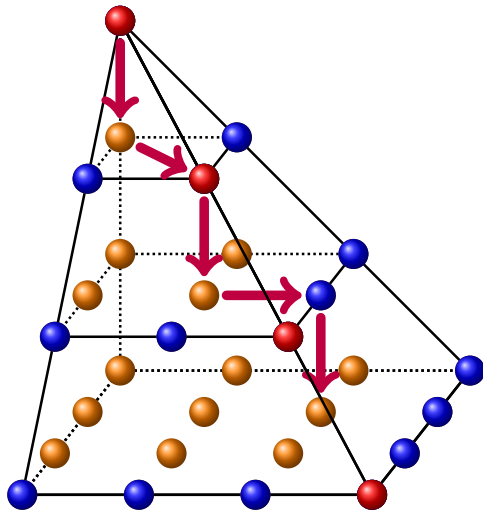
# Game dynamics: example

Firm 1 invests and becomes cost leader  $\rightsquigarrow (c_1, c_2, c) = (1, 2, 1)$



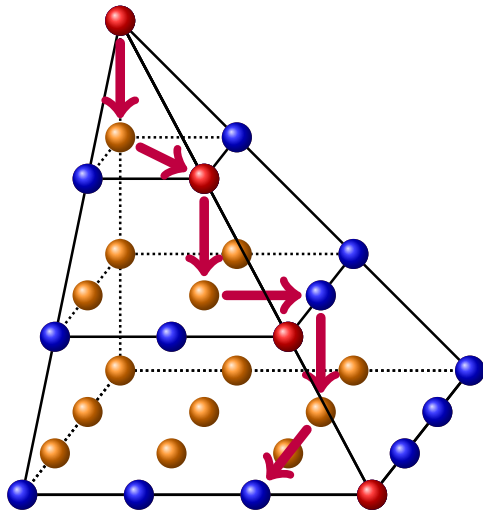
# Game dynamics: example

State-of-the-art technology becomes  $c = 0 \rightsquigarrow (c_1, c_2, c) = (1, 2, 0)$



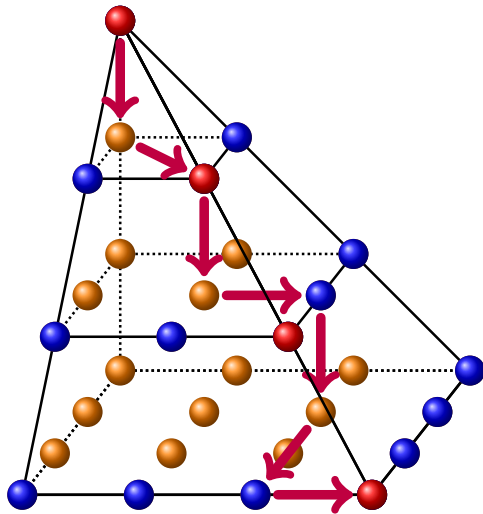
# Game dynamics: example

Firm 2 leapfrogs firm 1 to become new cost leader  $\rightsquigarrow (c_1, c_2, c) = (1, 0, 0)$



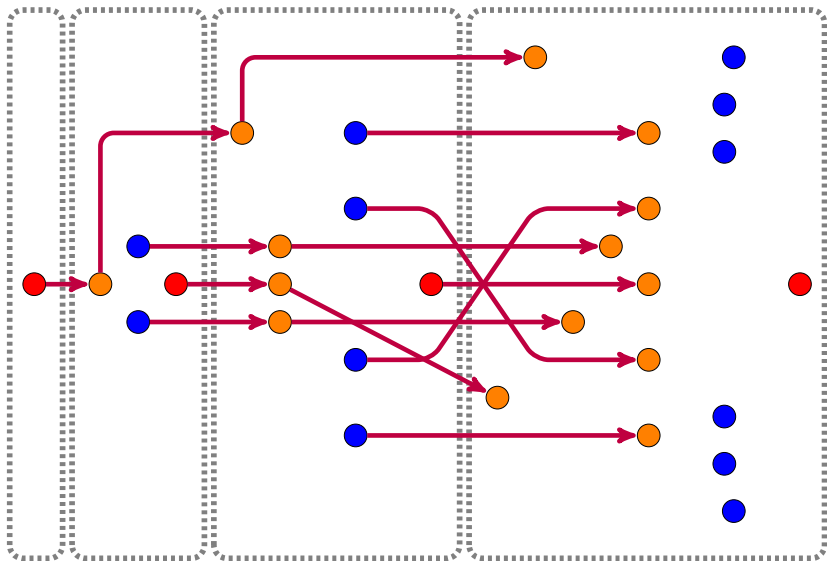
# Game dynamics: example

A particular sequence of investment decisions along technological progress pass



# Transitions due to technological progress

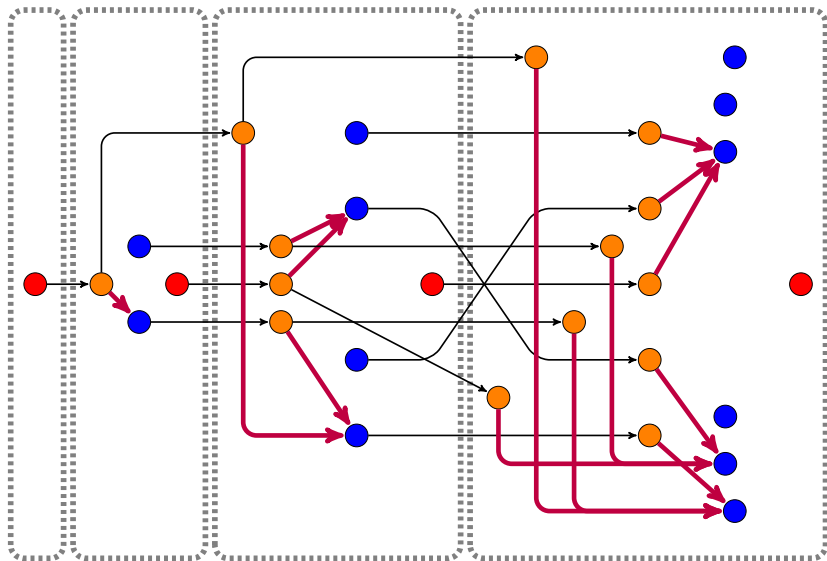
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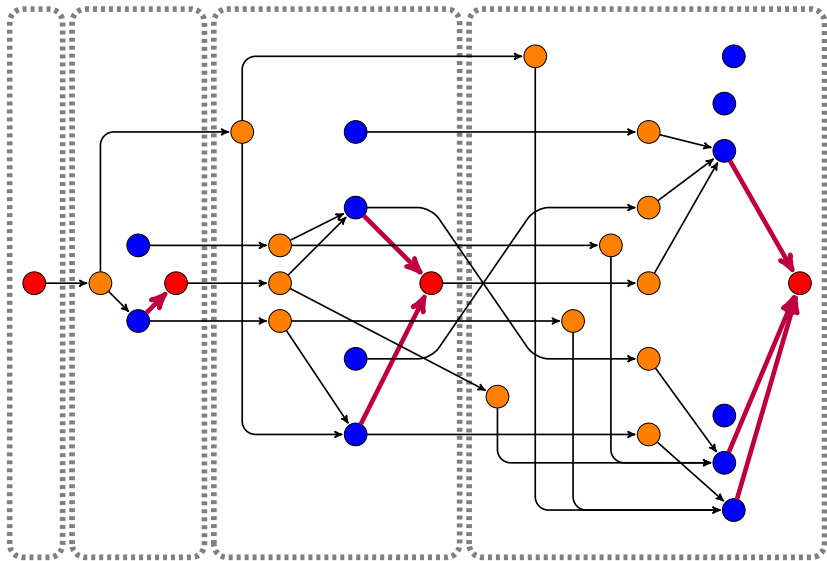
# Strategy-specific partial order on $S$

Strategy  $\sigma_1$  of firm 1: invest at all interior points



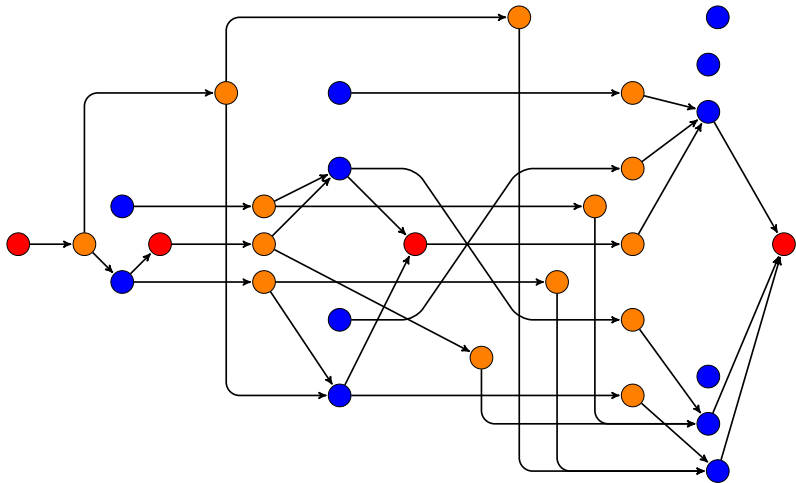
# Strategy-specific partial order on $S$

Strategy  $\sigma_2$  of firm 2: invest at all edge points



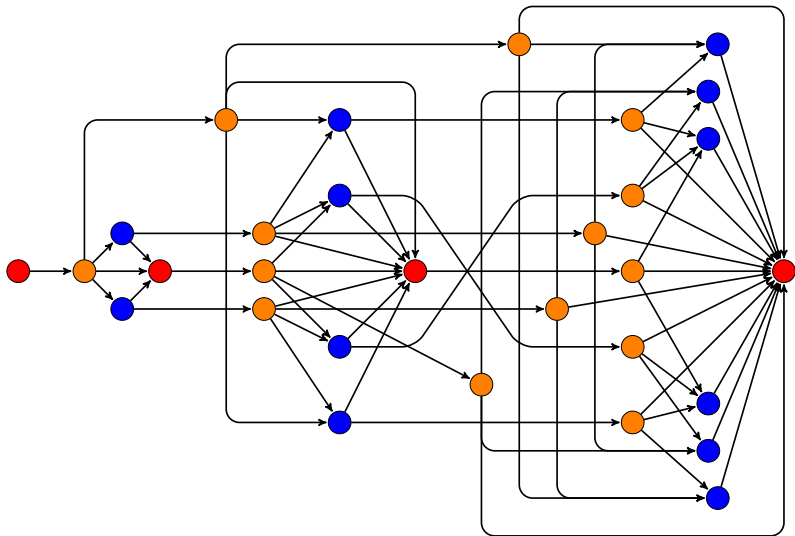
# Strategy-specific partial order on $S$

Strategy  $\sigma = (\sigma_1, \sigma_2)$  of both firms



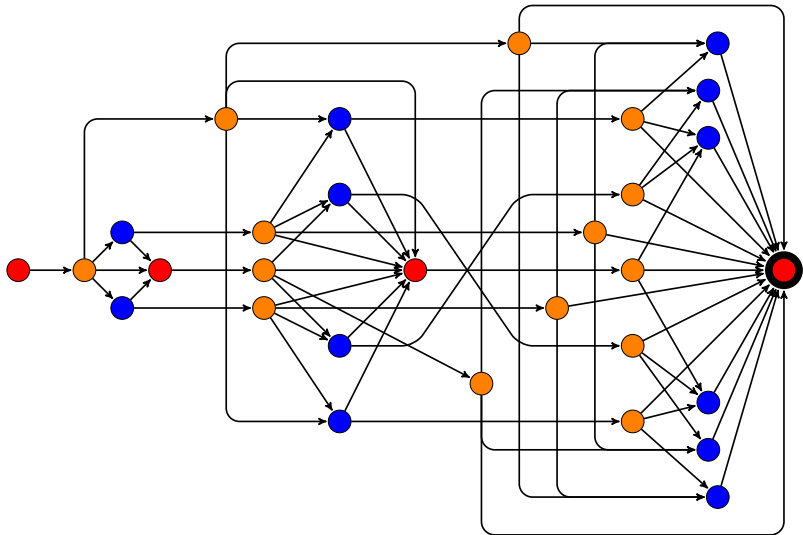
# Digraph of strategy independent partial order on $S$

Over all feasible strategies



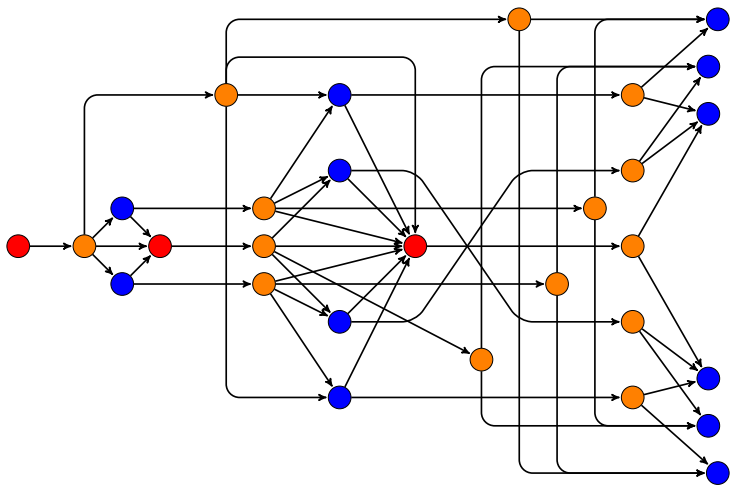
# Topological sort of game graph

Identify terminal states



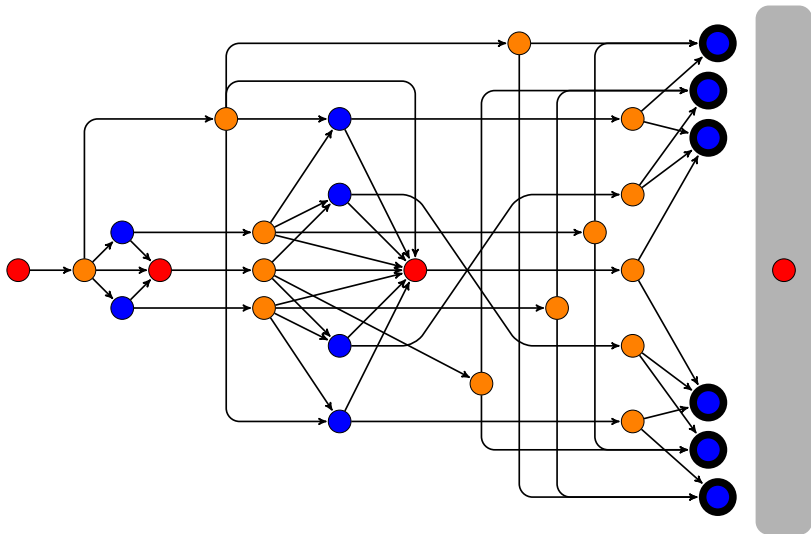
# Topological sort of game graph

Remove terminal states



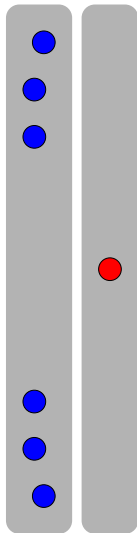
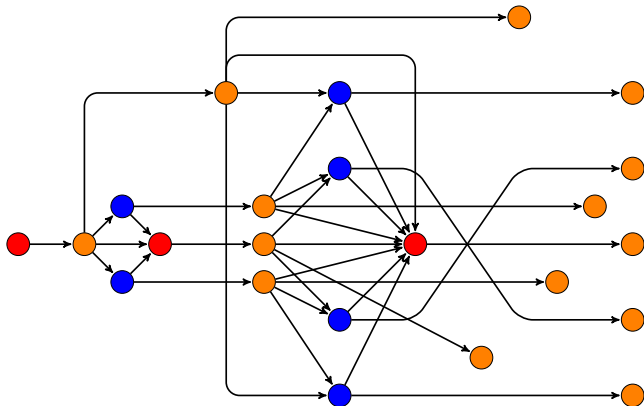
## Topological sort of game graph

### Identify terminal states



# Topological sort of game graph

Remove terminal states



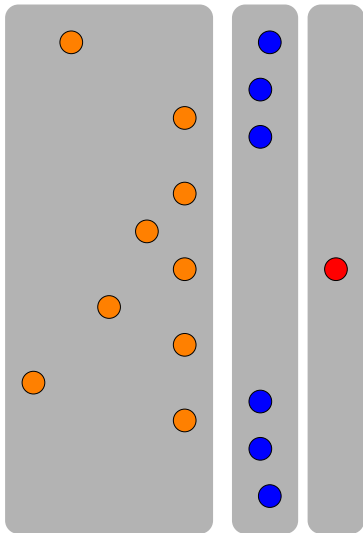
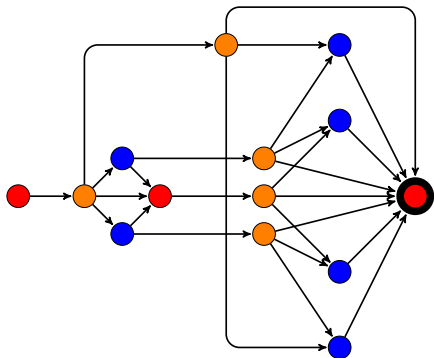






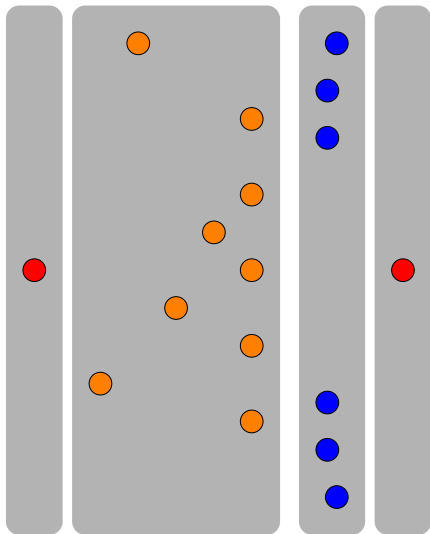
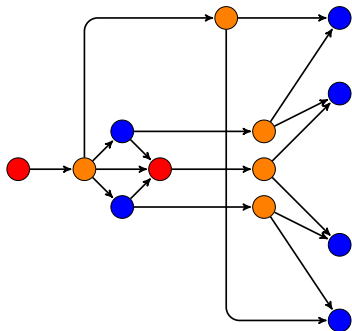
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# Topological sort of game graph

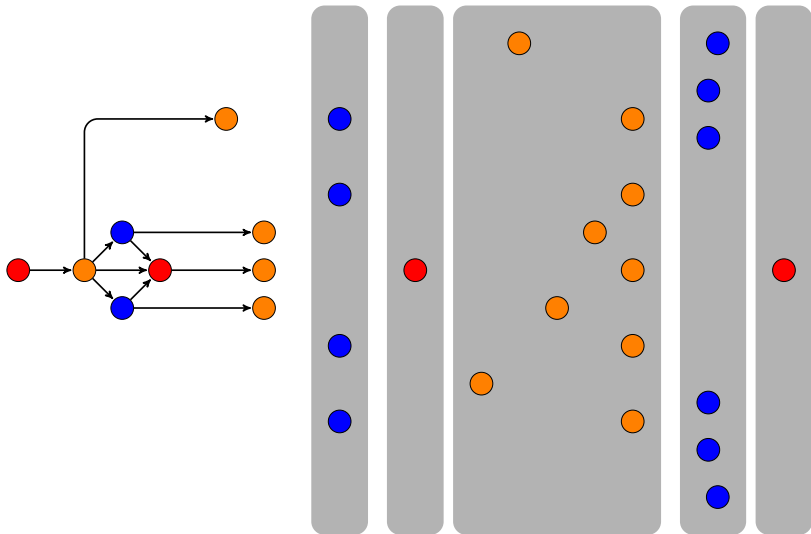
Remove terminal states





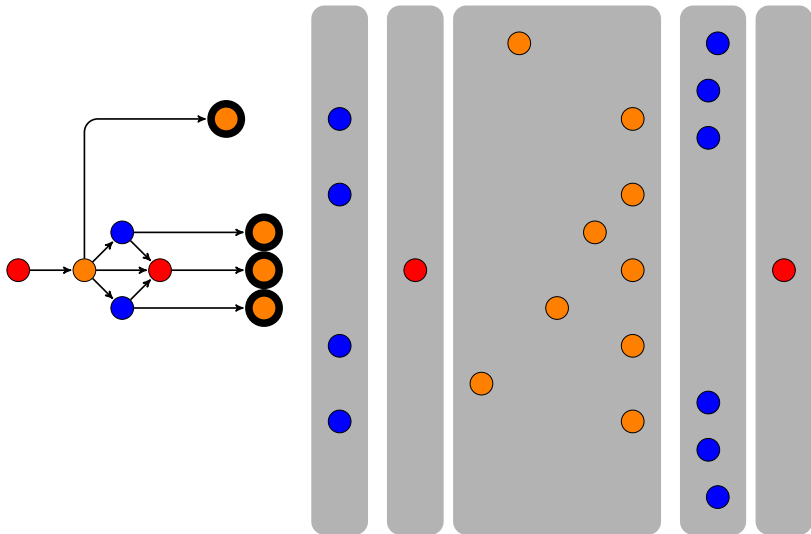
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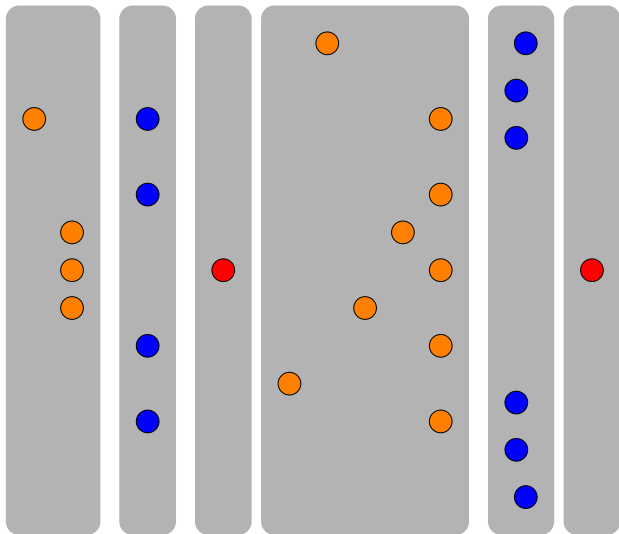
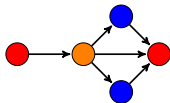
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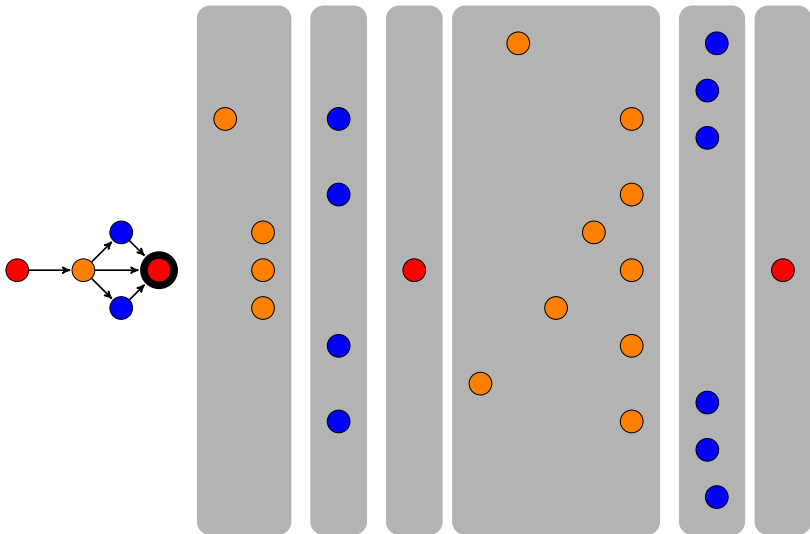
Remove terminal states





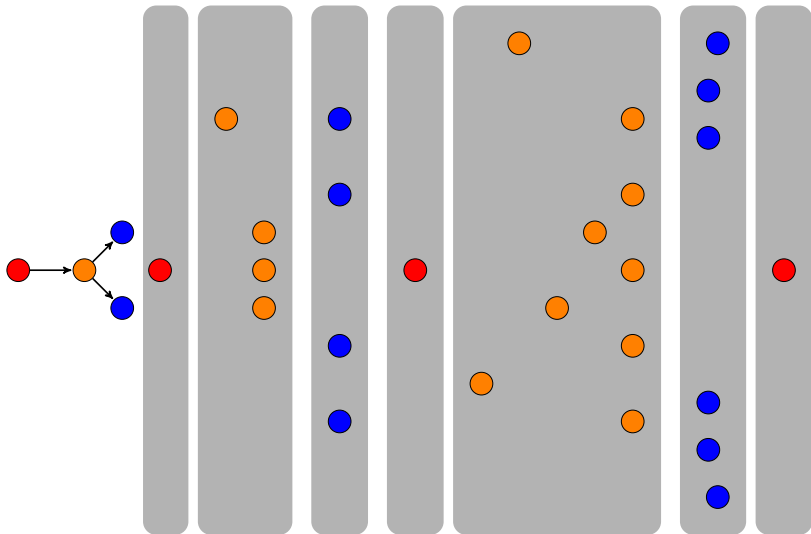
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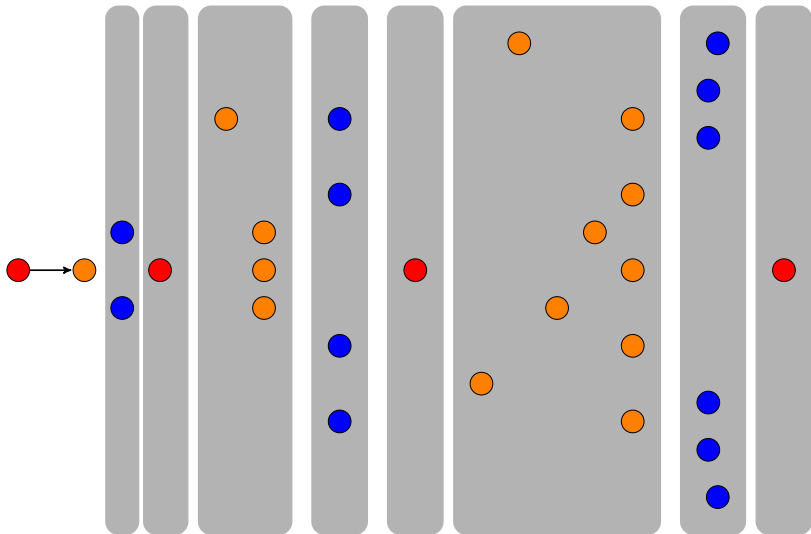
Remove terminal states





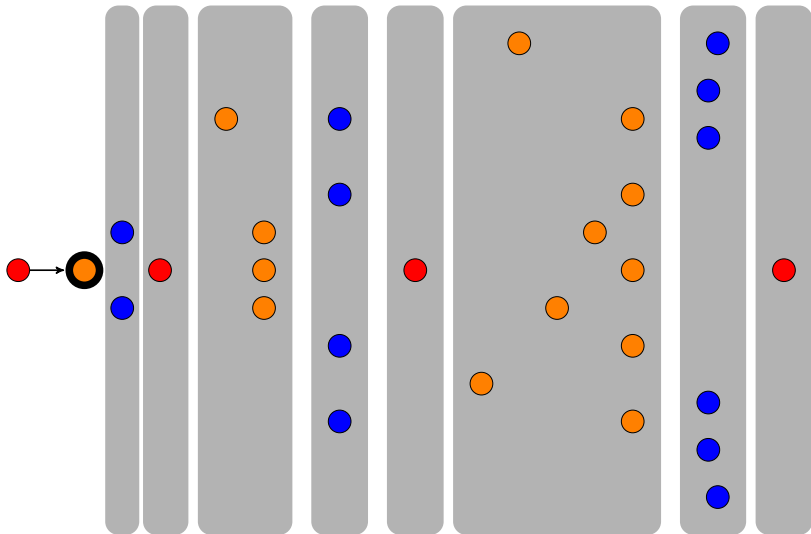
# Topological sort of game graph

Remove terminal states



# Topological sort of game graph

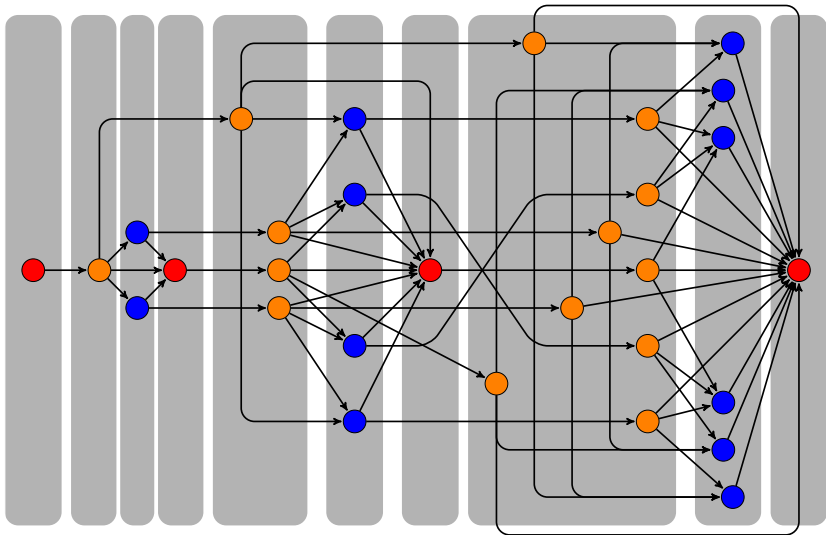
Identify terminal states





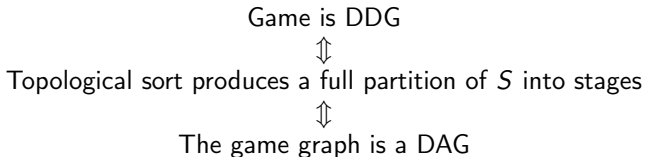
# Total order on the set of stages

After running a topological sort algorithm on the DAG



## Directional dynamic games and DAG

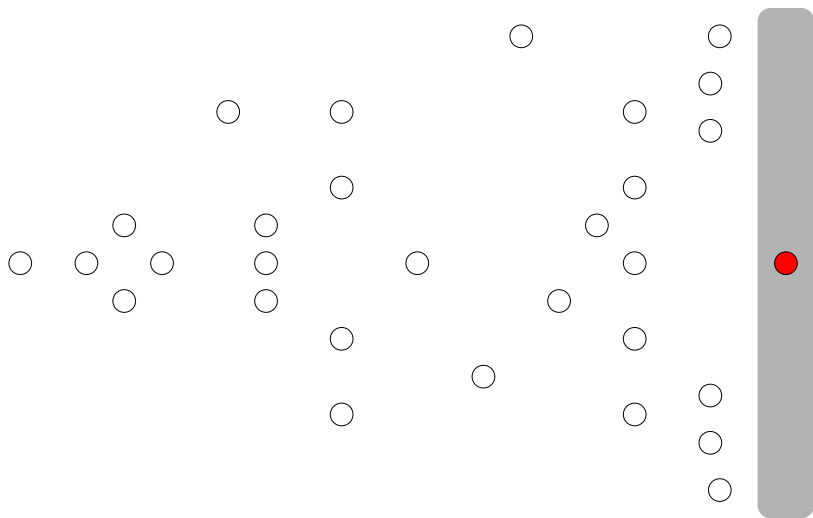
- ▶  $S$  is finite  $\implies$  Topological sort completes in finite number of steps
- ▶ If null-graph is reached after  $K$  iterations, then the game graph is a DAG and  $S$  is partitioned into  $K$  stages
- ▶ If the algorithm stops and there are still edges in the remaining graph, then there are **cycles** in the game graph





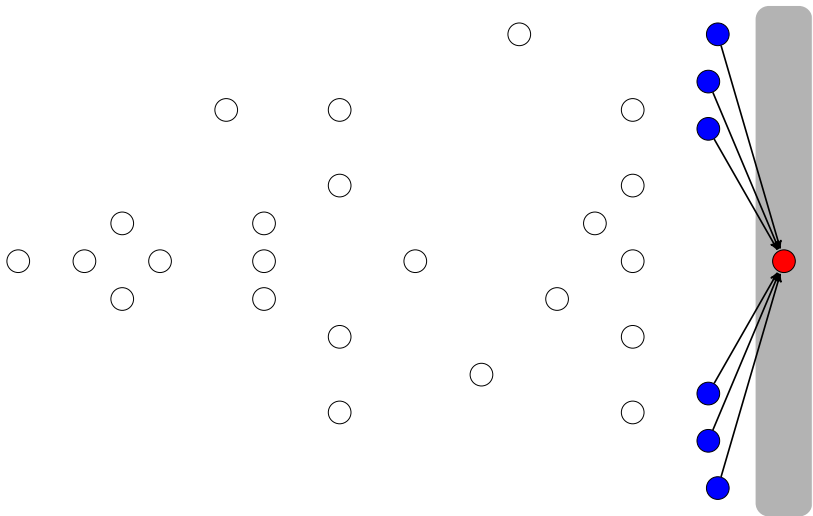
# State recursion algorithm

Backward induction on stages of DDG



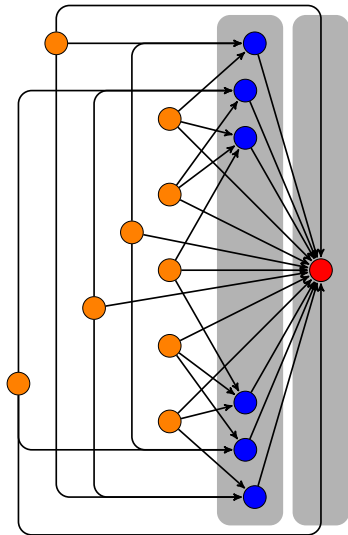
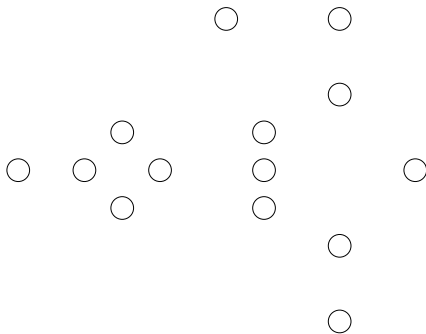
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Backward induction on stages of DDG



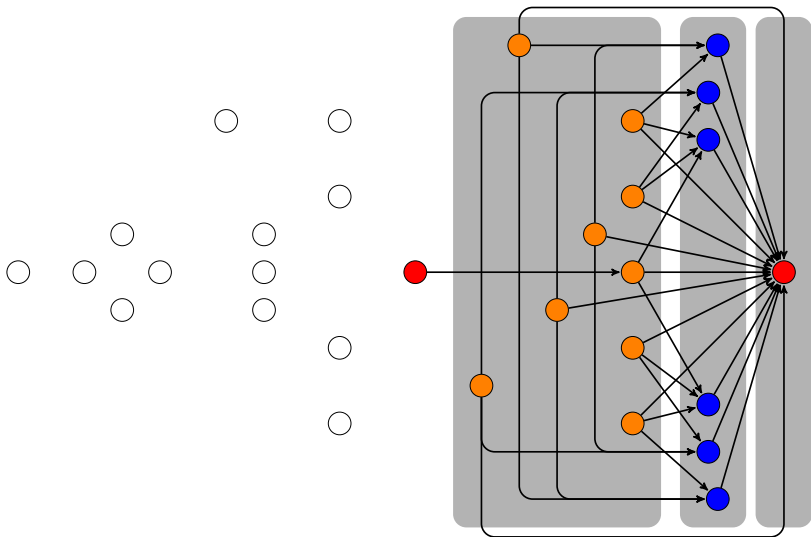
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# State recursion algorithm

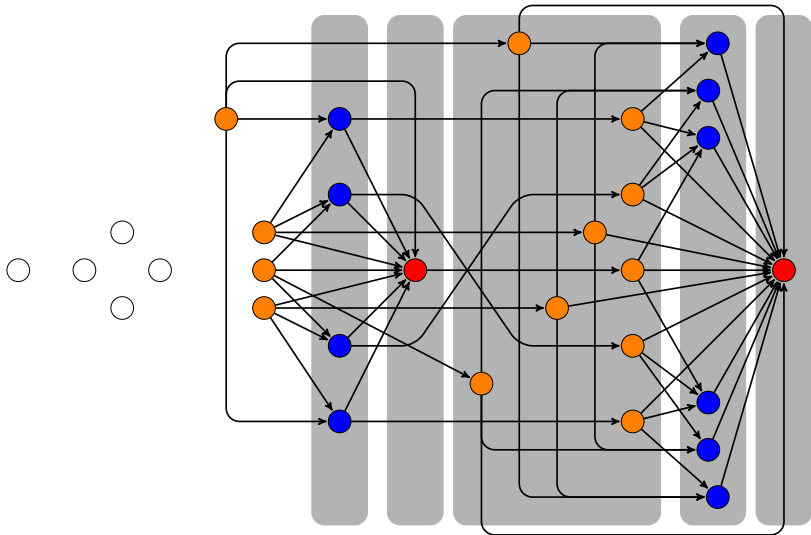
Backward induction on stages of DDG





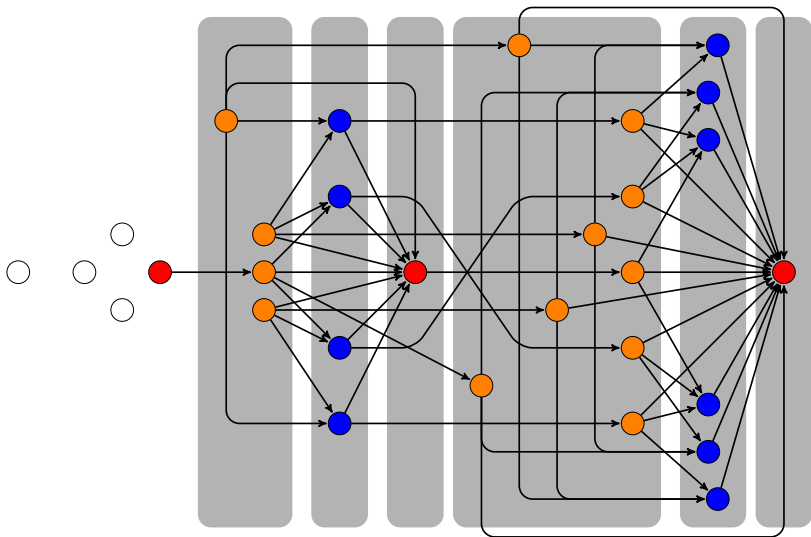
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Backward induction on stages of DDG



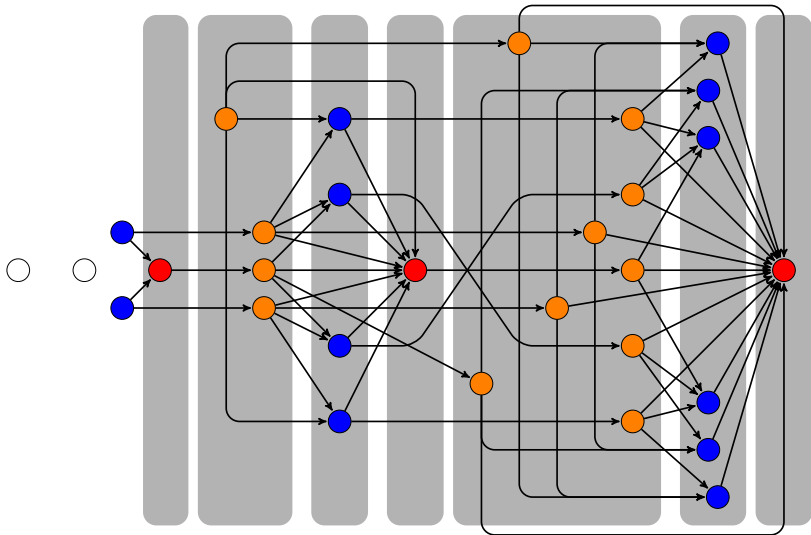
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Backward induction on stages of DDG



# State recursion algorithm

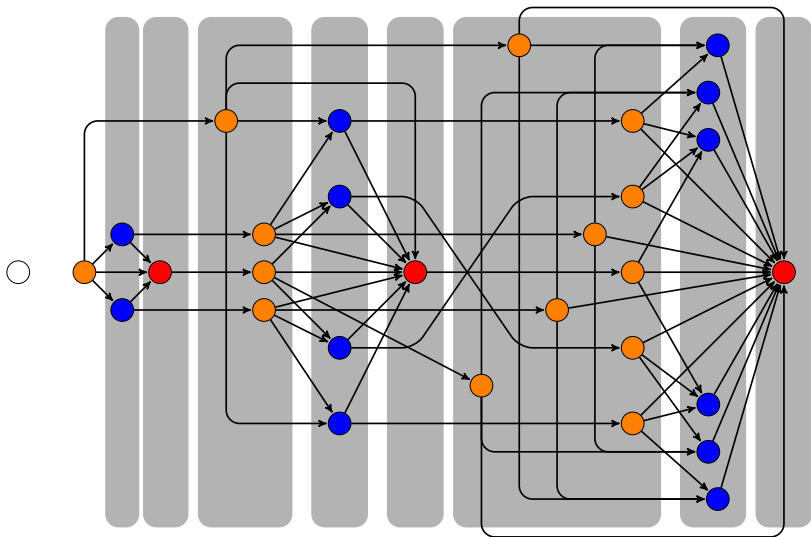
Backward induction on stages of DDG



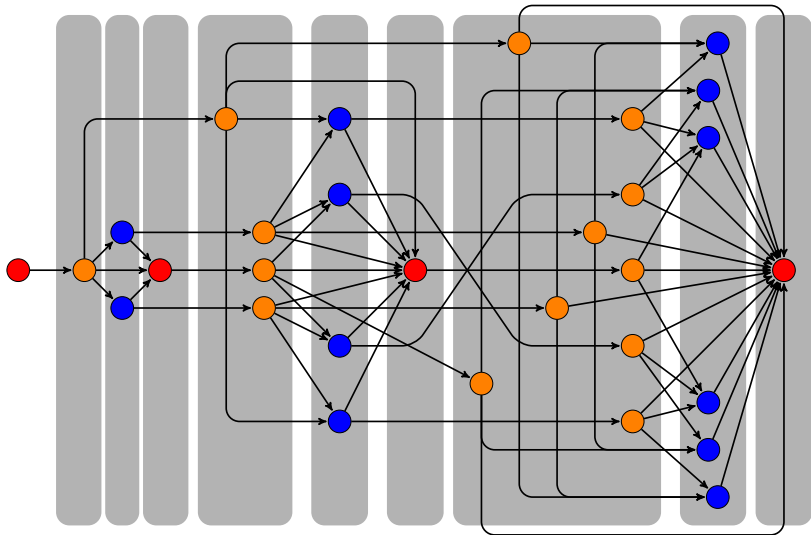


# State recursion algorithm

Backward induction on stages of DDG

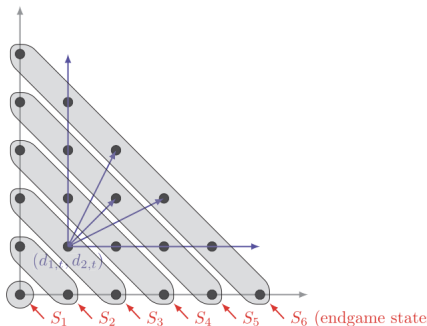
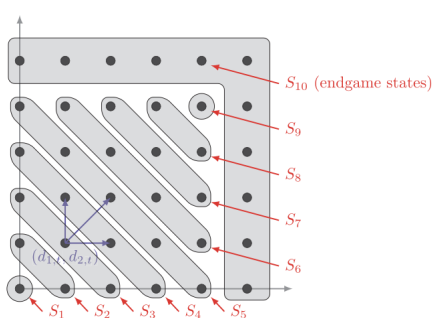


## State recursion algorithm



# Examples of Directional Dynamic Games

Many games have state dynamic evolutions described by a DAGs



Judd, Schmedders, Yeltekin (2012), *IER*

“Optimal rules for patent researchers”



Dube, Hitsch, Chintagunta (2010), *Marketing Science*

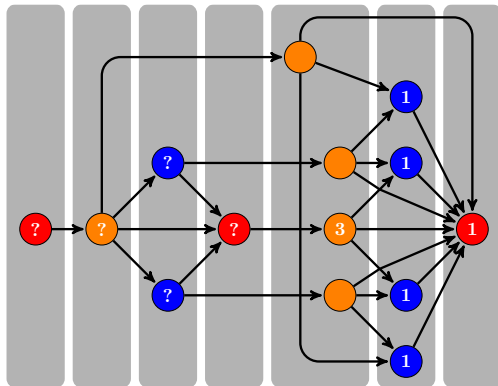
“Tipping and concentration in markets with indirect network effects”



# Multiplicity of stage equilibria

Number of equilibria in the higher stages depends on the selected equilibria

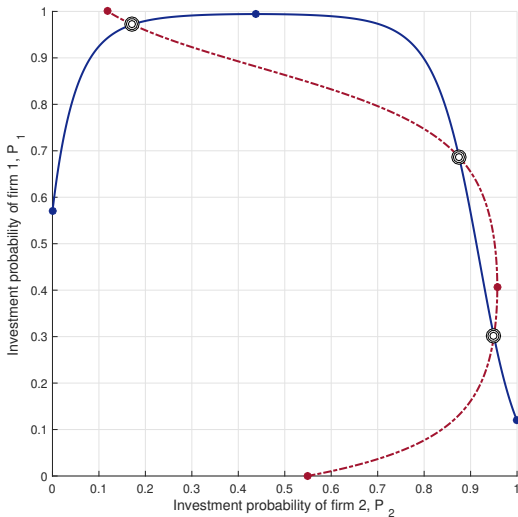
- ▶ State recursion proceeds **conditional on** equilibrium selection rule
- ▶ Multiplicity of stage equilibria  $\Leftrightarrow$  multiplicity
- ▶ Can systematically combine different stage equilibria



# Best response functions

Typically one or three stage equilibria, but may be 5

- Smooth best response function with  $\eta > 0$



# Recursive Lexicographic Search Algorithm

Building blocks of RLS algorithm:

1. State recursion algorithm solves the game **conditional on** equilibrium selection rule (ESR)
2. RLS algorithm efficiently cycles through **all feasible** ESRs

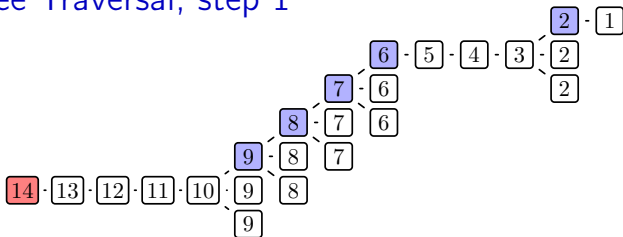
## Challenge:

- ▶ Choice of a particular MPE for any stage game at any stage
- ▶ may alter the **set** and even the **number** of stage equilibria at earlier stages

**Solution:** RLS = **depth-first tree traversal** (illustration coming)

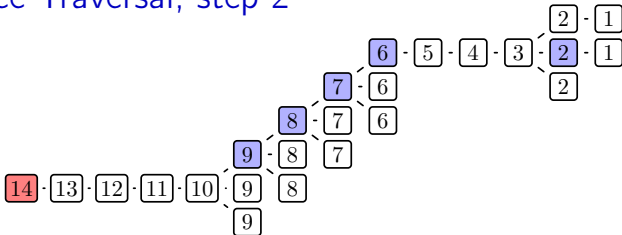
- ▶ Root of the tree is one of the absorbing states
- ▶ Levels of the tree correspond to the state points
- ▶ Branching happens when stages have multiple equilibria
- ▶ MPE of the game is given by a path from root to a leaf

## RLS Tree Traversal, step 1

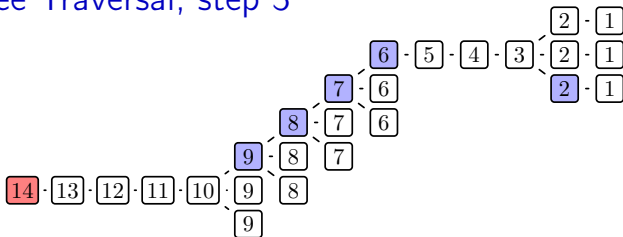




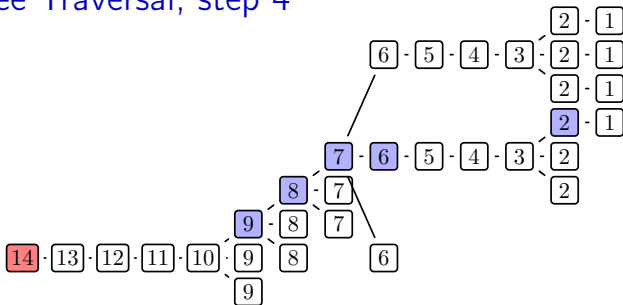
## RLS Tree Traversal, step 2



## RLS Tree Traversal, step 3



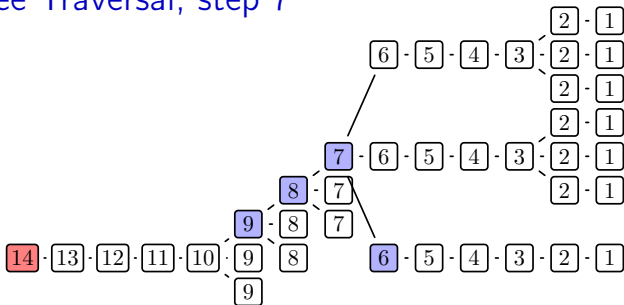
## RLS Tree Traversal, step 4



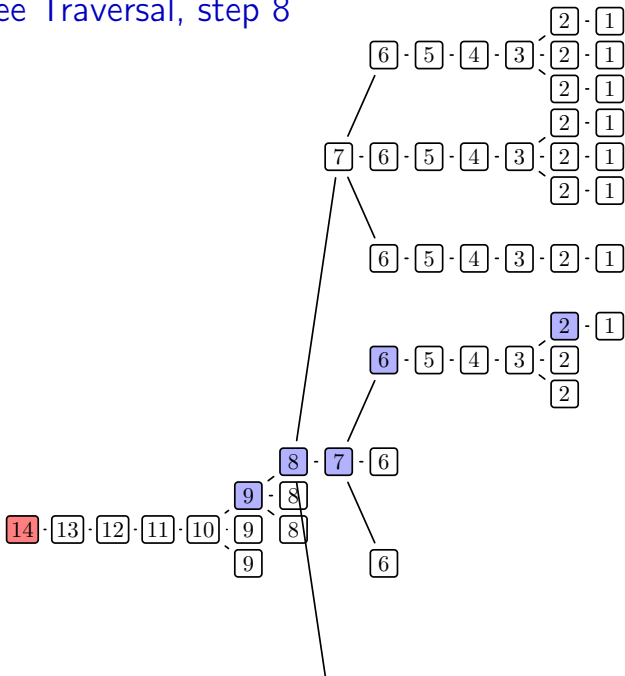




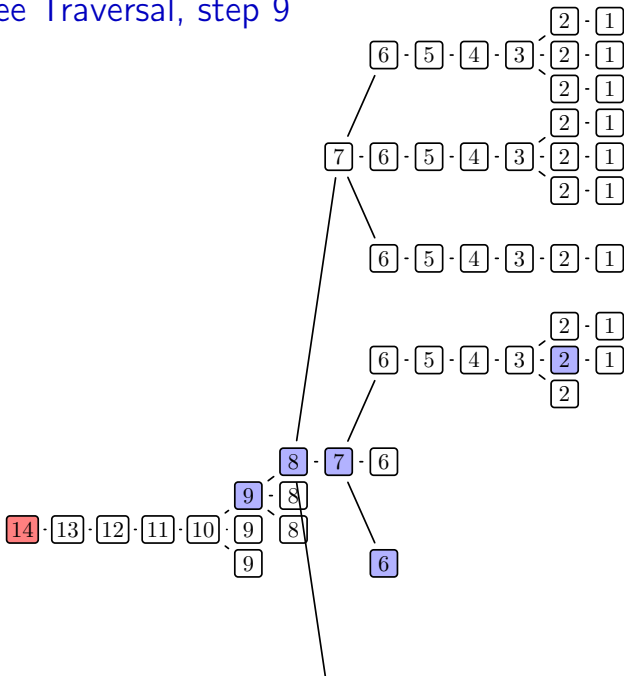
## RLS Tree Traversal, step 7



## RLS Tree Traversal, step 8



## RLS Tree Traversal, step 9





# Recursive Lexicographic Search (RLS) algorithm

## Theorem (RLS theorem)

*Assume there exists an algorithm that can find all MPE of every stage game of the DDG, and that the number of these equilibria is finite in every stage game.*

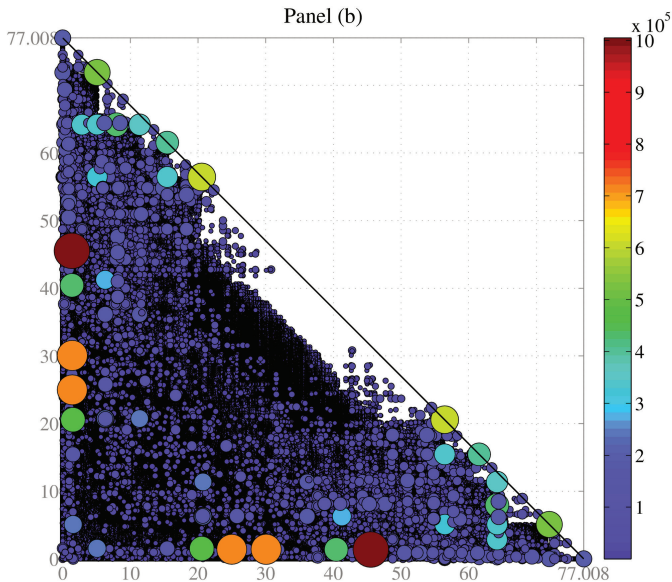
*Then the RLS algorithm finds all MPE of the DDG in a finite number of steps, which equals the total number of MPE.*



Iskhakov, Rust and Schjerning, 2016, ReStud

“Recursive lexicographical search: Finding all markov perfect equilibria of finite state directional dynamic games.”

# Simultaneous move leapfrogging: 164,295,079 equilibria



# ROAD MAP

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  - ▶ Bertrand pricing and investment game
  - ▶ Solving once: State recursion algorithm
  - ▶ Solving for all MPE: Recursive lexicographical search (RLS) algorithm
2. Structural estimation of DDGs: nested MLE RLS
  - ▶ Is it even feasible computationally?
3. Monte Carlo to compare to existing estimators in dynamic games (two-step CCP, NPL, EPL, MPEC)
  - ▶ One equilibrium in the model and data
  - ▶ Multiplicity of equilibria at true parameter
  - ▶ Multiple equilibria in the data

# Nested Recursive Lexicographical Search (NRLS)

- ▶ Data from  $M$  independent markets from  $T$  periods

$$Z = \{\bar{a}^{mt}, \bar{x}^{mt}\}_{m \in \{1, \dots, M\}, t \in \{1, \dots, T\}}$$

- ▶ Let the set of all MPE equilibria be  $\mathcal{E} = \{1, \dots, K(\theta)\}$

## 1. Outer loop

Maximization of the likelihood function w.r.t. to **structural parameters**  $\theta$

$$\theta^{ML} = \arg \max_{\theta \in \Theta} \mathcal{L}(Z, \theta)$$

## 2. Inner loop

Maximization of the likelihood function w.r.t. equilibrium selection

$$\mathcal{L}(Z, \theta) = \max_{k \in \{1, \dots, K(\theta)\}} \mathcal{L}(Z, \theta, P_{\theta}^k)$$

Max of a function on a discrete set organized into RLS tree

## Likelihood over the state space

- ▶ Given **equilibrium**  $k$  choice probabilities  
 $P_\theta^k(a|x) = (P_1^k(a|x, \theta), \dots, P_N^k(a|x, \theta))$ , likelihood is

$$\mathcal{L}(Z, \theta, P_\theta^k) = \frac{1}{M} \sum_{m=1}^M \sum_{t=1}^T \sum_{i=1}^N \log P_i^k(\bar{a}_i^{mt} | \bar{x}^{mt}; \theta)$$

- ▶ Let  $\iota$  **index points in the state space**,  $\iota \in \{1, \dots, S\}$   
 $\iota = 1$  initial point,  $\iota = S$  the terminal (absorbing) state
- ▶ Denote  $n_\iota$  the number of observations in state  $x_\iota$  and  $n_\iota^{a_i}$  the number of observations of player  $i$  taking action  $a_i$  at  $x_\iota$

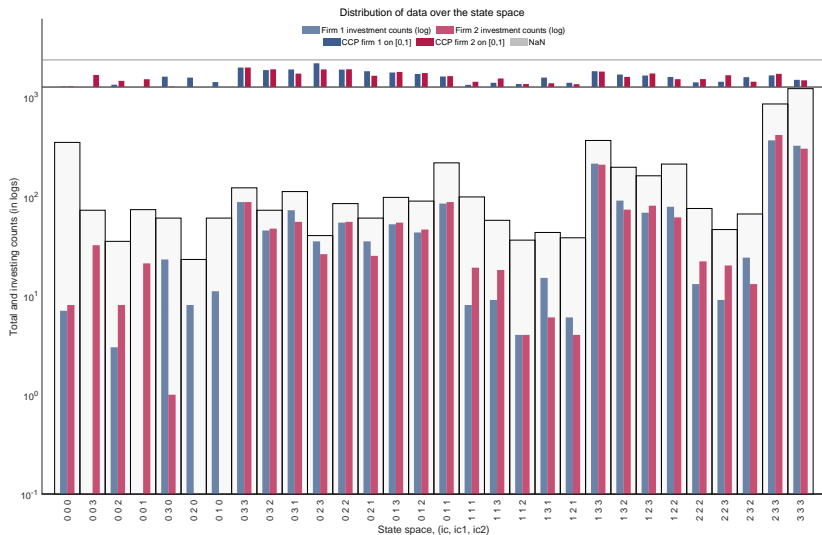
$$n_\iota = \sum_{m=1}^M \sum_{t=1}^T \mathbb{1}\{\bar{x}^{mt} = x_\iota\} \quad n_\iota^{a_i} = \sum_{m=1}^M \sum_{t=1}^T \mathbb{1}\{\bar{a}_i^{mt} = a_i, \bar{x}^{mt} = x_\iota\}$$

- ▶ Then equilibrium-specific likelihood can be computed as

$$\mathcal{L}(Z, \theta, P_\theta^k) = \frac{1}{M} \sum_{\iota=1}^S \sum_{i=1}^N \sum_a n_\iota^{a_i} \log P_i^k(a|x_\iota; \theta)$$

# Data distribution over the state space

1000 markets, 5 time periods, init at apex of the pyramid



# Branch and bound (BnB) method

Old method for solving integer programming problems

1. Form a **tree** of subdivisions of the set of admissible plans  
 $\implies$  **RLS tree**
2. Specify a **bounding function** representing the best attainable objective on a given subset (branch)  
 $\implies$  **Partial likelihood function** computed on the subset of states

$$\mathcal{L}^{\text{part}}(\mathbf{Z}^{\mathcal{S}}, \theta, V_{\theta}^k) = \sum_{\iota \in \mathcal{S}} \sum_{i=1}^N \sum_a n_{\iota}^{a_i} \log P_i^k(a | x_{\iota}; \theta)$$

where  $\mathbf{Z}^{\mathcal{S}} = \{(a, x) : x \in \mathcal{S} \subset \{1, \dots, S\}\}$  denotes data on  $\mathcal{S}$

- ▶ Monotonic decreasing in cardinality of  $\mathcal{S}$   
(declines as more data is added)
  - ▶ Equals to the full log-likelihood on the full state space when  $\mathbf{Z}^{\mathcal{S}} = \mathbf{Z}$   
(at the leaf of RLS tree)
3. Dismiss the subsets of the plans where the bound is below the current best attained value of the objective



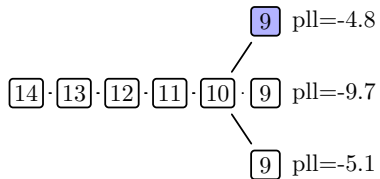
Land and Doig, 1960 *Econometrica*

## BnB on RLS tree, step 1

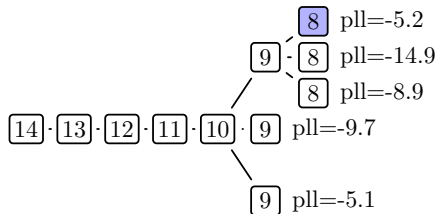
$\boxed{14} \cdot \boxed{13} \cdot \boxed{12} \cdot \boxed{11} \cdot \boxed{10}$  Partial loglikelihood = -3.2



## BnB on RLS tree, step 2

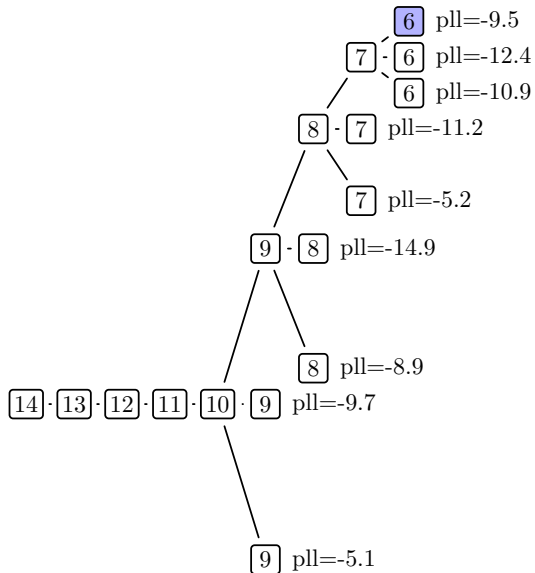


## BnB on RLS tree, step 3

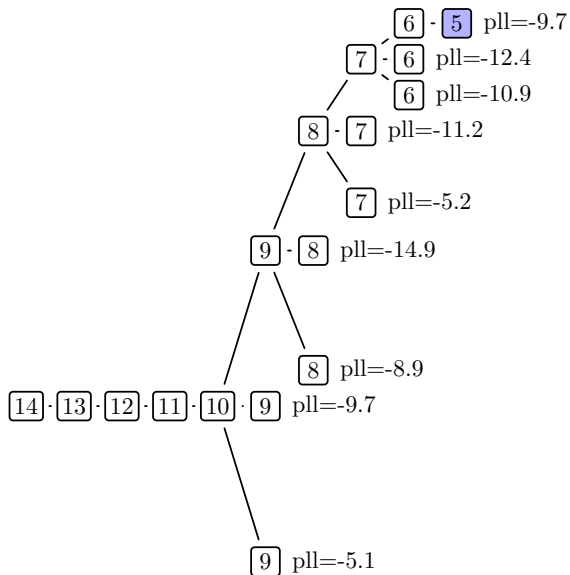




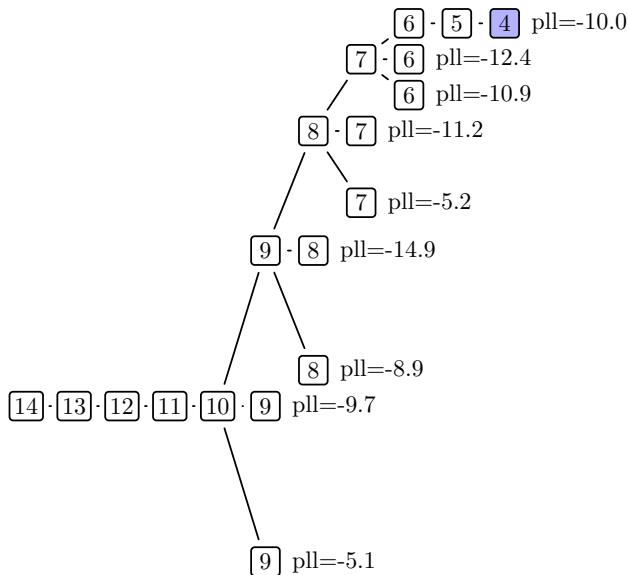
## BnB on RLS tree, step 5



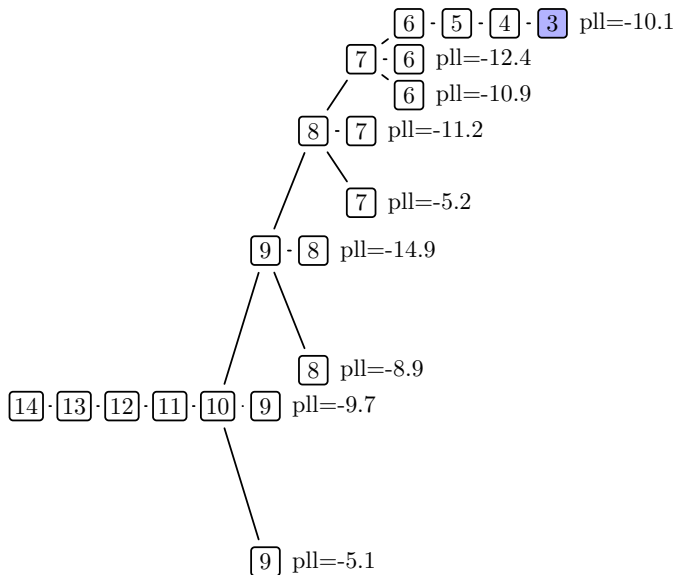
## BnB on RLS tree, step 6



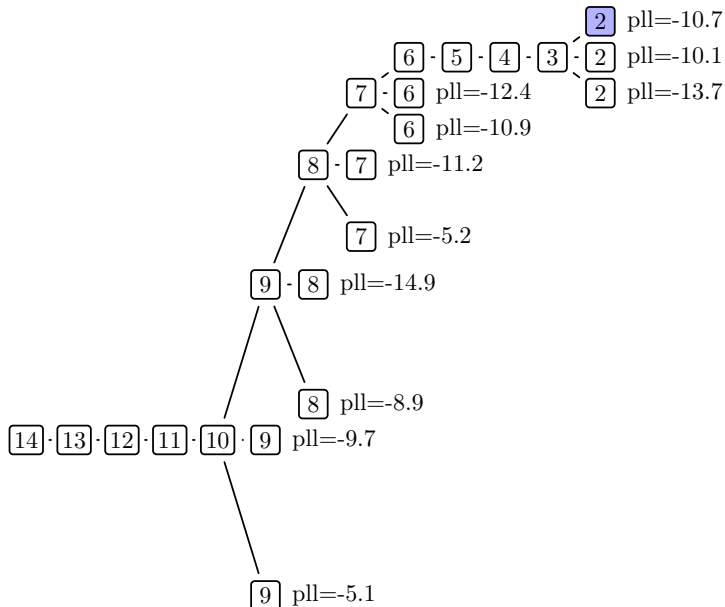
## BnB on RLS tree, step 7



## BnB on RLS tree, step 8

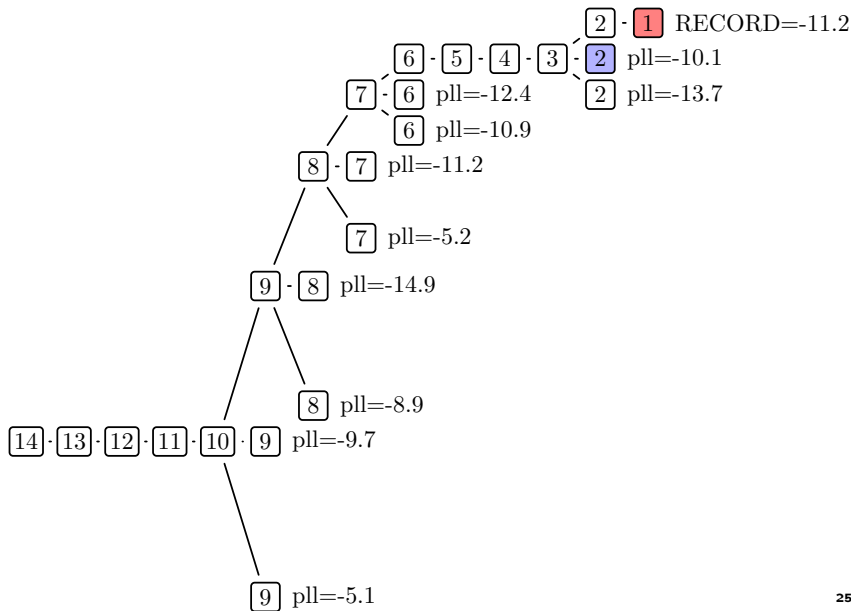


## BnB on RLS tree, step 9

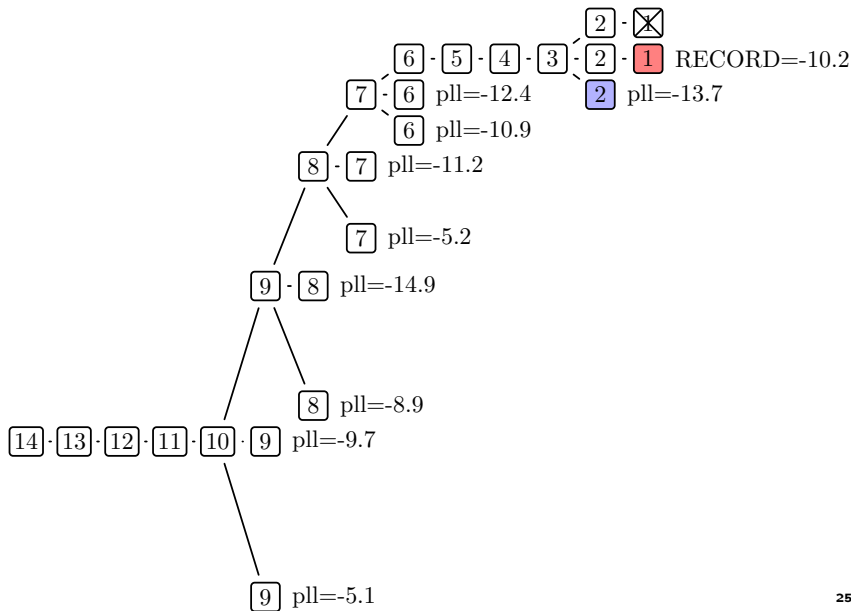




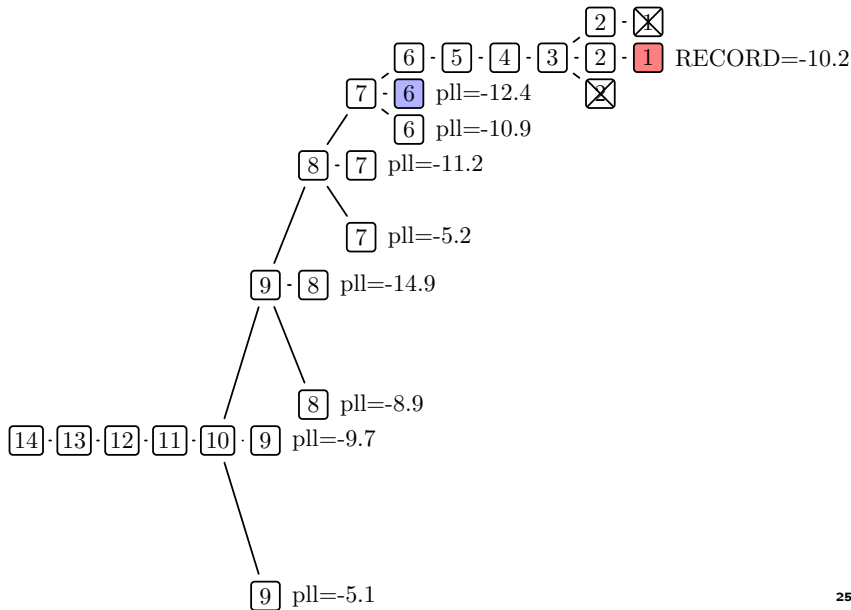
## BnB on RLS tree, step 10



# BnB on RLS tree, step 11

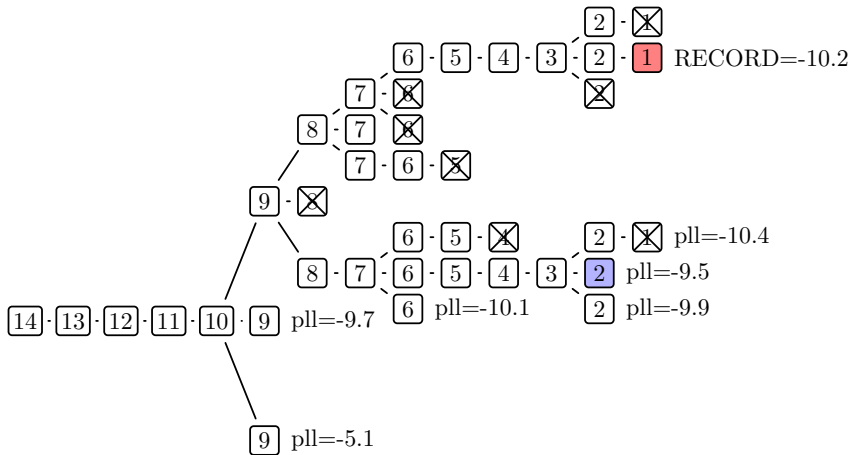


## BnB on RLS tree, step 12

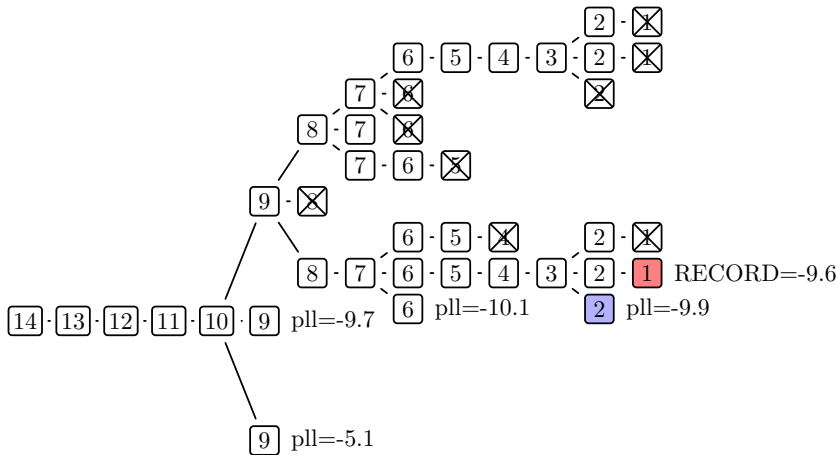




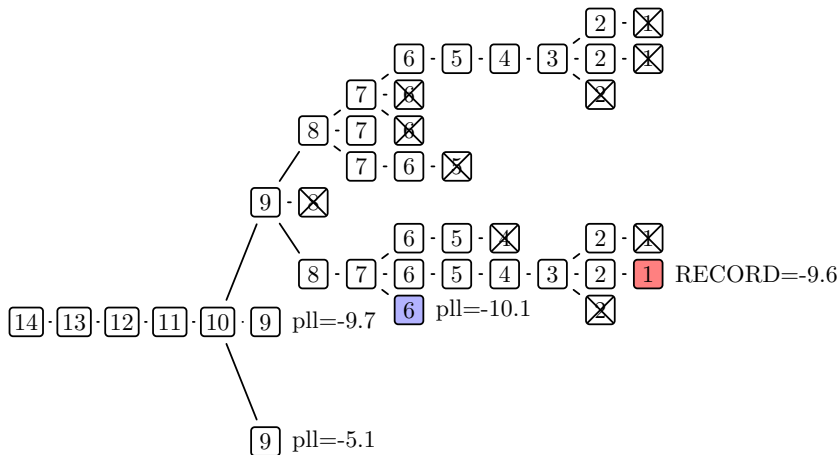
## BnB on RLS tree, step 29



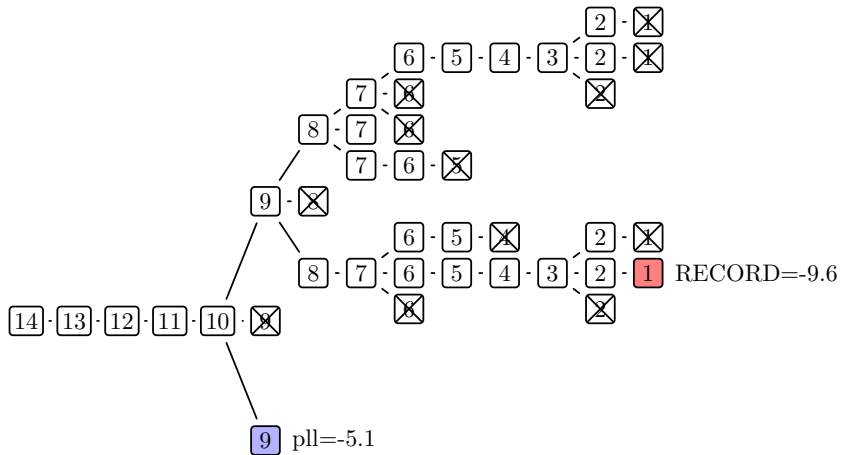
## BnB on RLS tree, step 30



# BnB on RLS tree, step 31

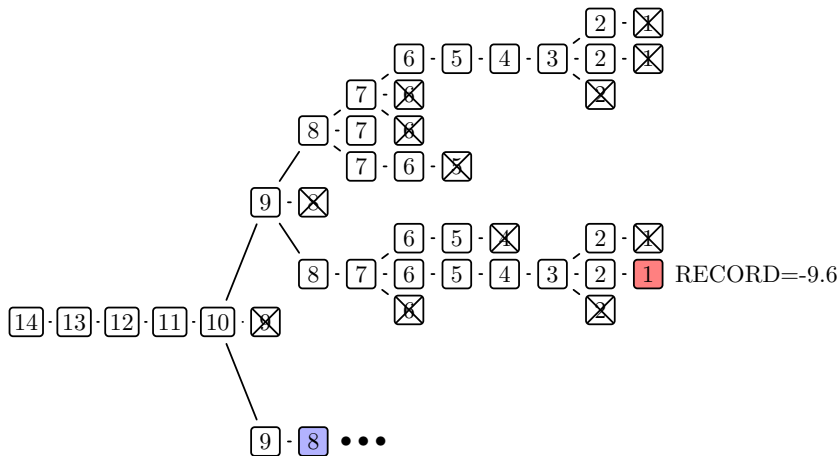


## BnB on RLS tree, step 33





## BnB on RLS tree, step 34



# Non-parametric likelihood bounding

- ▶ **Idea**: augment the partial likelihood bounding function with non-parametric likelihood computed on the “rest of the data”
- ▶ Parametric choice probabilities  $P_i^k(a|x_\ell; \theta) \rightarrow$  frequencies  $n_\ell^{a_i}/n_\ell$

$$\mathcal{L}^{\text{non-par}}(Z^S) = \sum_{\ell \in S} \sum_{i=1}^N \sum_a n_\ell^{a_i} \log(n_\ell^{a_i}/n_\ell)$$

- ▶  $\mathcal{L}^{\text{non-par}}(Z^S)$  depends only on the **counts** from the data!
- ▶ Not hard to show **algebraically** that for any  $Z^S$  ( $\approx$  Gibbs inequality)

$$\mathcal{L}^{\text{non-par}}(Z^S) > L^{\text{part}}(Z^S, \theta, P_\theta^k) \quad \forall S$$

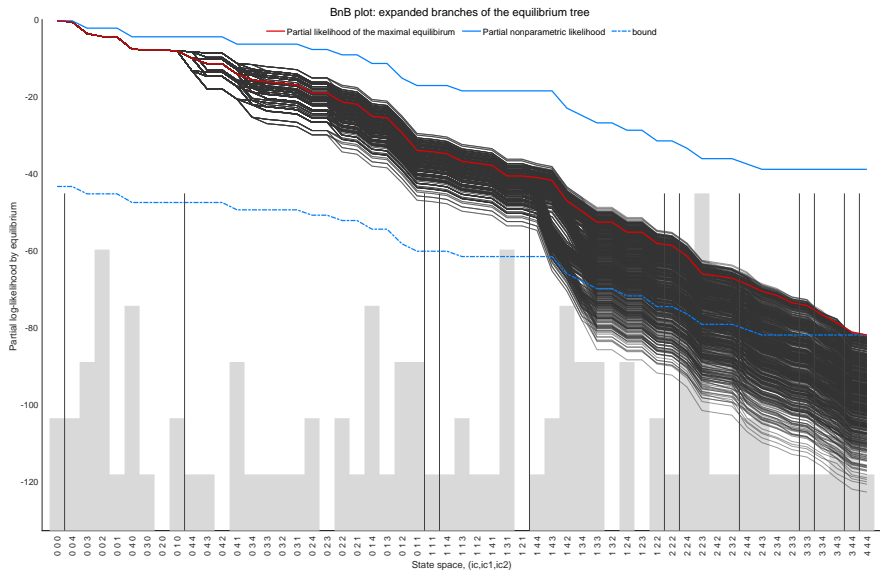
- ▶ Therefore partial likelihood can be **optimistically extrapolated** by empirical likelihood at any step  $\ell$  of the RLS tree traversal

$$\mathcal{L}^{\text{part}}(Z^{\{S, S-1, \dots, \ell\}}, \theta, P_\theta^k) + \mathcal{L}^{\text{non-par}}(Z^{\{\ell-1, \dots, 1\}})$$

- ▶ **Augmented partial likelihood is much more powerful bound for BnB**

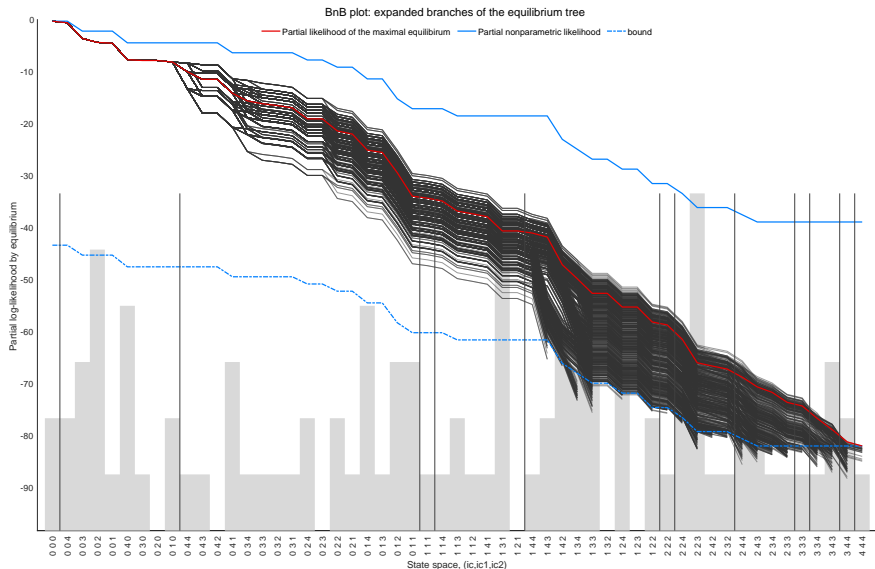
# Non-parametric likelihood bounding

$\iota = S = 14$  (terminal state) on the left,  $\iota = 1$  (initial state) on the right



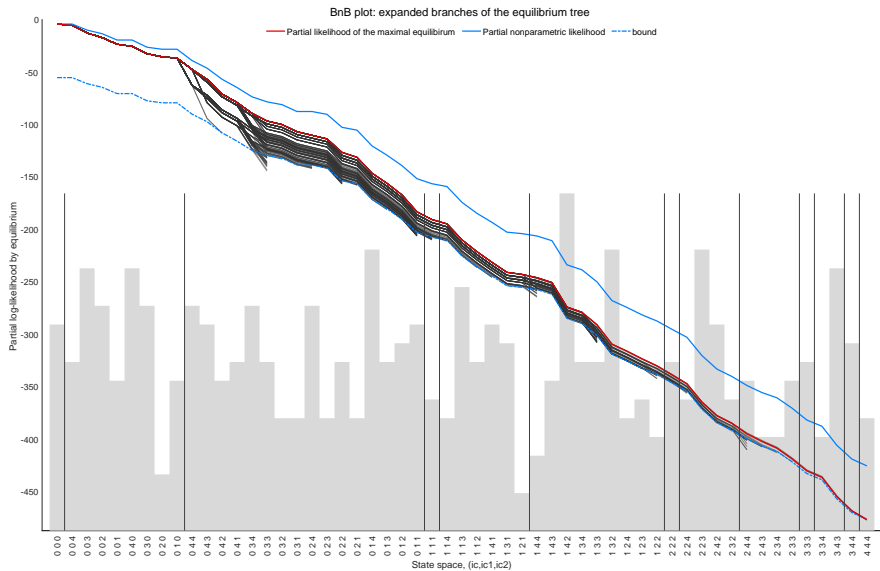
# BnB with non-parameteric likelihood bound

Greedy traversal + non-parameteric likelihood bound

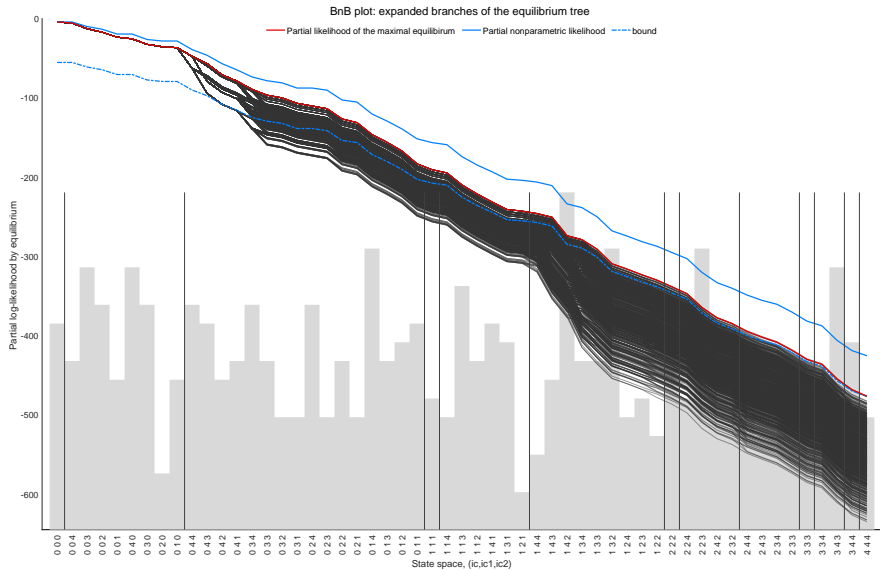


# BnB with non-parameteric likelihood bound, larger sample

Non-parametric  $\rightarrow$  parametric likelihood as  $N \rightarrow \infty$  at true  $\theta \Rightarrow$  even less computation



## Full enumeration RLS in larger sample



## BnB refinement with non-parametric likelihood

- ▶ For any amount of data the non-parametric likelihood is greater or equal to the parametric likelihood *algebraically*
- ▶ BnB augmented with non-parameteric likelihood bound gives sharper Bounding Rules  $\rightarrow$  less computation
- ▶ With more data as  $M \rightarrow \infty$
- ▶ Non-parametric log-likelihood converges to the true partial likelihood (assuming the model is well-specified and in the neighborhood of the true parameter)
- ▶ The width of the band between the blue lines in the plots decreases
  - $\rightarrow$  Even sharper Bounding Rules
  - $\rightarrow$  Even less computation
  - $\rightarrow$  Still delivering exact maximum

MLE for any sample size, but much easier to compute with more data!

# ROAD MAP

1. Solving directional dynamic games (DDGs):
  - ▶ Simple example: Bertrand pricing and investment game
  - ▶ State recursion algorithm
  - ▶ Recursive lexicographical search (RLS) algorithm
2. Structural estimation of DDGs using Nested RLS
  - ▶ Branch-and-bound on RLS tree
  - ▶ Non-parametric likelihood bounding
3. Monte Carlo: (Compare NRLS, two-step CCP, NPL, EPL, MPEC)
  - ▶ One equilibrium in the model and data
  - ▶ Multiplicity of equilibria at true parameter
  - ▶ (Multiple equilibria in the data)



# Monte Carlo simulations

A

---

Single equilibrium in the model  
One equilibrium in the data

Implementation details:

- ▶ Leapfrogging model with  $N = 2$  Bertrand competitors deciding whether to invest in cost-reducing technology (IRS, 2016)
- ▶  $k_1$  parameter in investment cost function
- ▶  $M = 1000$ ,  $T = 5$
- ▶ All methods are initialized with 2-step CCP estimator

B

---

Multiple equilibria in the model  
Same equilibrium played the data

C

---

Multiple equilibria in the model  
Multiple equilibria in the data:

- ▶ Long panels, each market plays their own equilibrium
- ▶ Groups of markets play the same equilibrium

## Monte Carlo A: no multiplicity

Number of equilibria at true parameter: 1

Number of equilibria in the data: 1

	2step	NPL	EPL	MPEC-VP	MPEC-P	NRLS
True $k_1 = 3.5$	3.52786	3.49714	3.49488	3.49488	3.49486	3.49488
Bias	0.02786	-0.00286	-0.00512	-0.00512	-0.00514	-0.00512
MCSD	0.10037	0.06522	0.07042	0.07042	0.07078	0.07042
ave log-like	-1.16661	-1.16144	-1.16143	-1.16143	-1.16139	-1.16143
log-likelihood	-5833.07	-5807.21	-5807.16	-5807.16	-5806.95	-5807.16
log-like short	-	-0.050	-0.000	-0.000	-0.000	-0.000
KL divergence	0.03254	0.00021	0.00024	0.00024	0.00024	0.00024
$  P - P_0  $	0.11270	0.00469	0.00495	0.00495	0.00500	0.00495
$  \Psi(P) - P  $	0.16185	0.0000	0.0000	0.0000	0.0000	0.0000
$  \Gamma(v) - v  $	0.87095	0.00000	0.00000	0.00000	0.00000	0.00000
Converged of 100	-	100	100	100	99	100

- ▶ Equilibrium conditions satisfied (except 2step)
- ▶ Nearly all MLE estimators identical to the last digit
- ▶ NPL and EPL estimators approach MLE

## Monte Carlo B, run 1: little multiplicity

Number of equilibria at true parameter: 3

Number of equilibria in the data: 1

Data generating equilibrium: [stable](#)

	2step	NPL	EPL	MPEC-VP	MPEC-P	NRLS
True k1=7.5	7.55163	7.49844	7.49918	7.65318	7.35124	7.49919
Bias	0.05163	-0.00156	-0.00082	0.15318	-0.14876	-0.00081
MCS D	0.17875	0.06062	0.03413	0.99742	0.47136	0.03413
ave log-likelihood	-0.84779	-0.84425	-0.84421	-0.88682	-0.87541	-0.84421
log-likelihood	-21194.86	-21106.33	-21105.13	-22170.40	-21885.37	-21105.13
log-likelihood short	-	-1.206	-0.000	-1062.740	-776.809	-0.000
KL divergence	0.02557	0.00040	0.00013	0.23536	0.16051	0.00013
$  P - P_0  $	0.11085	0.00490	0.00280	0.17466	0.20957	0.00280
$  \Psi(P) - P  $	0.170940	0.000000	0.000000	0.000000	0.000000	0.000000
$  \Gamma(v) - v  $	1.189853	0.000000	0.000000	0.000000	0.000000	0.000001
N runs of 100	100	100	100	98	97	100

- ▶ MPEC convergence deteriorates
- ▶ Equilibrium conditions are satisfied, but estimators start to converge to *wrong* equilibria  
(as seen from KL divergence from the data generating equilibrium)

## Monte Carlo B, run 2: little multiplicity, unstable

Number of equilibria at true parameter: 3

Number of equilibria in the data: 1

Data generating equilibrium: **unstable**

	2step	NPL	EPL	MPEC-VP	MPEC-P	NRLS
True $k_1=7.5$	7.54238	7.39276	7.48044	7.73133	7.63100	7.50176
Bias	0.04238	-0.10724	-0.01956	0.23133	0.13100	0.00176
MCSD	0.17145	0.05608	0.15801	0.72988	0.89874	0.03820
ave log-like	-0.86834	-0.89374	-0.86550	-0.88512	-0.90196	-0.86504
log-likelihood	-21708.60	-22343.58	-21637.54	-22127.91	-22549.06	-21626.12
log-like short	-	-765.242	-11.413	-502.121	-920.643	-0.000
KL divergence	0.02271	0.15996	0.00257	0.11452	0.20182	0.00012
$  P - P_0  $	0.09757	0.20709	0.00619	0.03860	0.02504	0.00307
$  \Psi(P) - P  $	0.160102	0.000000	0.000000	0.000000	0.000000	0.000000
$  \Gamma(v) - v  $	1.126738	0.000000	0.000000	0.000000	0.000000	0.000001
N runs of 100	100	18	100	99	98	100

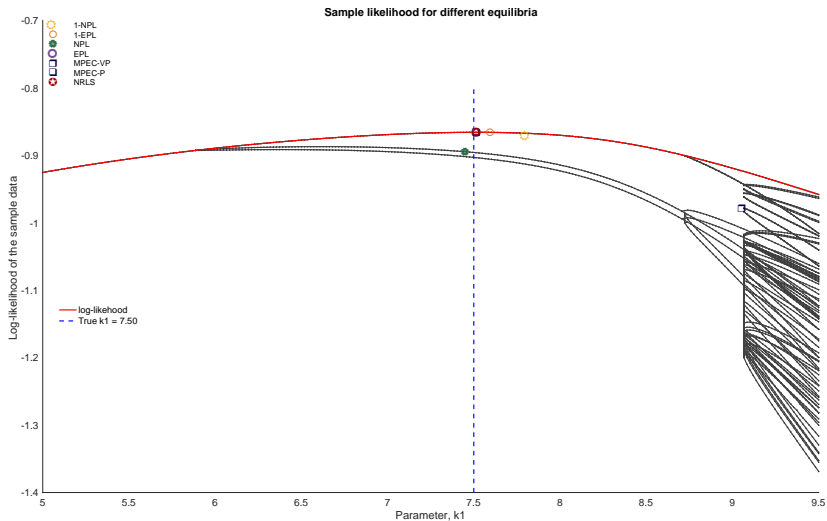
- ▶ NPL estimator fails to converge
- ▶ Similar convergence issues for MPEC
- ▶ EPL estimator performs well



Aguirregabiria, Marcoux (2021)

# Likelihood correspondence

Lines are constructed using symmetric KL-divergence



## Monte Carlo B: discontinuous likelihood

Number of equilibria at true parameter: 9

Number of equilibria in the data: 1

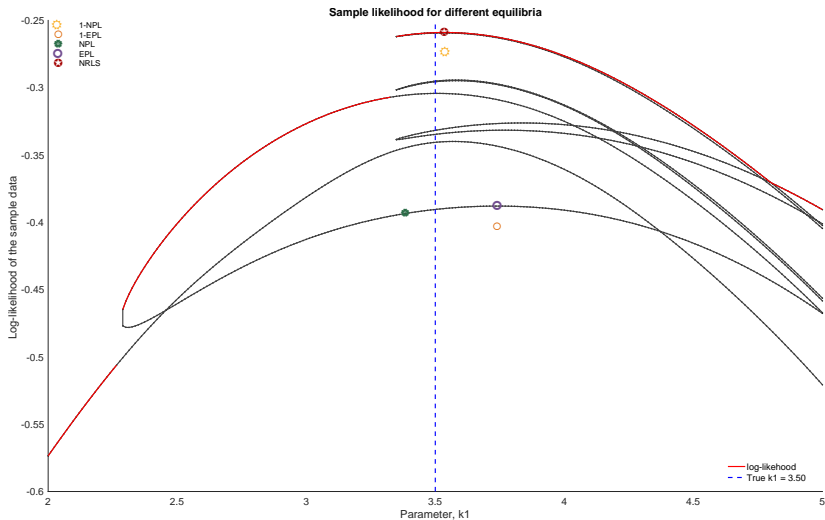
Data generating equilibrium: unstable, near “cliffs”

	2step	NPL	EPL	MPEC-VP	MPEC-P	NRLS
True k1=3.5	3.49739	3.55144	3.64772	3.65943	3.67027	3.50212
Bias	-0.00261	0.05144	0.14772	0.15943	0.17027	0.00212
MCS D	0.13999	0.07133	0.12900	0.12693	0.11583	0.03255
ave log-likelihood	-0.27494	-0.29474	-0.29528	-0.30330	-0.30257	-0.25086
log-likelihood	-1374.721	-1473.695	-1476.425	-1516.503	-1512.847	-1254.320
log-likelihood short	-	-219.375	-222.104	-270.999	-267.523	-0.000
KL divergence	0.01512	0.04889	0.04495	0.04102	0.04078	0.00016
$\ P - P_0\ $	0.62850	0.86124	0.83062	0.66562	0.65879	0.01610
$\ \Psi(P) - P\ $	0.763764	0.000000	0.000000	0.000000	0.000000	0.000002
$\ \Gamma(v) - v\ $	0.852850	0.000000	0.000000	0.000000	0.000000	0.000005
N runs of 100	100	100	100	28	27	100

- ▶ Equilibrium conditions are satisfied, but estimators converge to *wrong* equilibria as seen from KL divergence from DGP equilibria
- ▶ Biased estimates by EPL, NPL and MPEC (constraints are satisfied, yet low likelihood and high KL divergence)

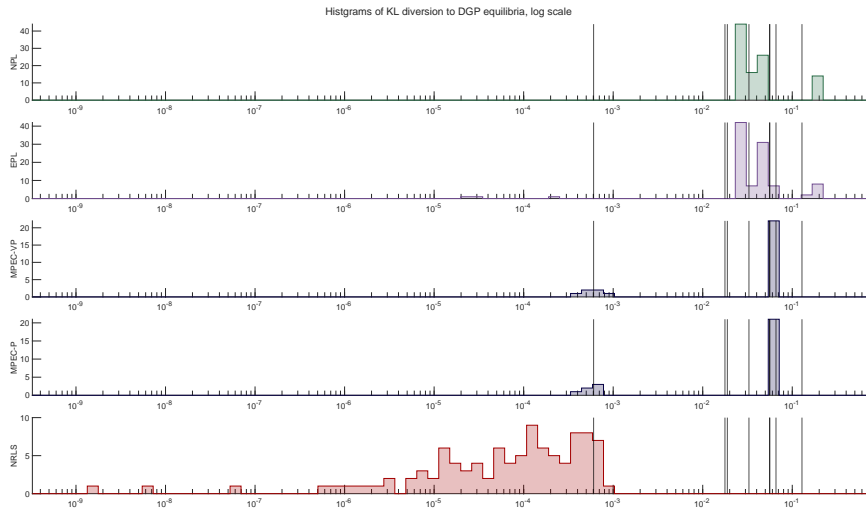
# Likelihood correspondence

Lines are constructed using symmetric KL-divergence



# Equilibrium selection estimates

Distribution of KL-divergence to the DGP equilibrium, vertical lines represent other equilibria





## Monte Carlo B: massive multiplicity

Number of equilibria at true parameter: 2455

Number of equilibria in the data: 1

Time to enumerate all equilibria (RLS) once: 10m 39s

	1-NPL	NPL	EPL	NRLS
True $k_1=3.75$	3.70959	3.71272	3.78905	3.74241
Bias	-0.04041	-0.03728	0.03905	-0.00759
MCS D	0.11089	0.06814	0.40716	0.03032
ave log-likelihood	-0.38681557	-0.37348793	-0.45256293	-0.35998461
log-likelihood	-1934.078	-1867.440	-2262.815	-1799.923
log-like shortfall	-	-66.529	-467.607	-0.000
KL divergence	Inf	14.07523	12231.59186	0.32429
$\ P - P_0\ $	0.82204	0.65580	0.79241	0.07454
$\ \Psi(P) - P\ $	0.963574	0.000000	0.000000	0.000006
$\ \Gamma(v) - v\ $	7.020899	0.000000	0.000000	0.000008
N runs of 100	100	18	68	100
CPU time	0.159s	11.262s	4.013s	4.731s

- ▶ Severe convergence problems for NPL and EPL
- ▶ Poor eqb identification (low likelihood and high KL divergence)
- ▶ NRLS has comparable CPU time (much faster than full enumeration)

# Monte Carlo C, multiple equilibria in the data

---

- ▶ Assume that **the same** equilibrium is played in each market **over time**
- ▶ Grouped fixed-effects, groups defined by the equilibria played

## 1. Joint grouped fixed-effects estimation

- ▶ Estimate the partition of the markets into groups playing different equilibria together with  $\theta$
- ▶ For each market compute maximum likelihood over all equilibria and “assign” it to the relevant group (estimation+classification)
- ▶ Computationally very demanding: BnB market-by-market, non-parametric refinement has no bite

## 2. Two-step grouped fixed-effects estimation

- ▶ Step 1: partition the markets based on some observable characteristics (K-means clustering) (Outside of Monte Carlo)
- ▶ Step 2: estimate  $\theta$  allowing different equilibria in different groups
- ▶ **Small additional computational cost for NRLS!**



Bonhomme, Manresa (2015); Bonhomme, Lamadon, Manresa (2022)

## Monte Carlo C: multiple equilibria in the data

Number of equilibria at true parameter: 81

Number of equilibria in the data: 5

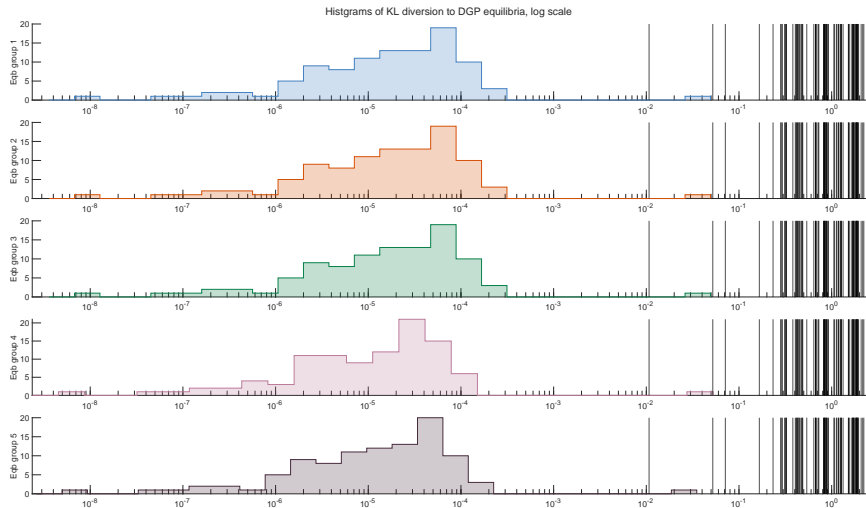
Number of unique equilibria in the data: 3

	1-NPL	NRLS				
True $k_1=9.25$	9.20991	9.25449				
Bias	-0.04009	0.00449				
MCS D	0.15021	0.04109				
ave log-likelihood	-0.798223	-0.707174				
log-likelihood	-19955.57	-17679.36				
log-like shortfall	-	0.000				
KL divergence	0.32943	0.00039	0.00039	0.00039	0.00040	0.00028
$\ P - P_0\ $	0.32787	0.00287	0.00287	0.00287	0.00252	0.00240
$\ \Psi(P) - P\ $	0.460870	0.000000	0.000000	0.000000	0.000000	0.000000
$\ \text{Bellman}(V) - V\ $	5.438776	0.000000	0.000000	0.000000	0.000000	0.000000
# converged of 100	100	100				
CPU time, sec	0.023	20.695				

- ▶ All 5 equilibria were identified correctly as seen from KL divergence
- ▶ The first three equilibria are the same in DGP, and have the same KL and L1 divergence
- ▶ Similar results in runs with many more equilibria in the data

# Equilibrium selection estimates

Distribution of KL-divergence to the DGP equilibrium, vertical lines represent other equilibria



## Monte Carlo C, run 2: many more equilibria in the data

Number of equilibria at true parameter: 19,683

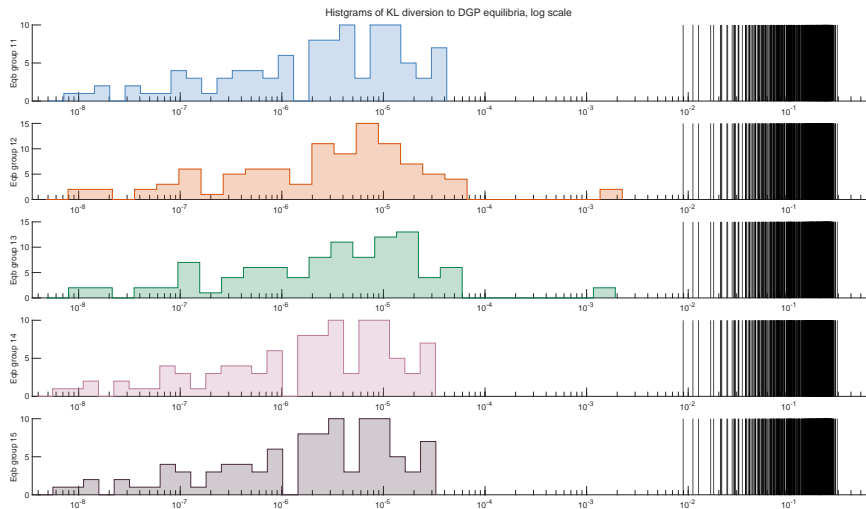
Number of equilibria in the data: 25

	1-NPL	EPL	NRLS
True $k_1=9.5$	9.12069	9.40900	9.49992
Bias	0.03918	-0.09100	-0.00008
MCSD	0.02864	0.05586	0.00414
ave log-likelihood	-0.511188	-0.515356	-0.504482
log-likelihood	-25559.42	-25767.79	-25224.10
log-like shortfall	-	-543.690	0.000
KL divergence	0.05753	0.05045	0.0 to 0.0001
$\ P - P_0\ $	0.18517	0.26430	0.00059 to 0.00572
$\ \Psi(P) - P\ $	0.186981	0.000000	0.0 for all
$\ \text{Bellman}(V) - V\ $	2.577006	0.000000	0.0 for all
# converged of 100	100	100	100
CPU time, sec	0.047	1.041	3m 9.4s

- ▶ All 25 equilibria were identified correctly
- ▶ Largest average KL divergence  $10^{-4}$  whereas the closest to DGP equilibrium at true  $\theta$  has  $\text{KL}=10^{-2}$
- ▶ Largest error in choice probabilities across the state space 0.00572

# Equilibrium selection estimates

Distribution of KL-divergence to the DGP equilibrium, vertical lines represent other equilibria



Shown are the first five identified equilibria, other twenty are similar

# NRLS estimator for directional dynamic games

Complicated computational task involving maximization over the large finite set of all MPE equilibria → **branch-and-bound algorithm with refined bounding rule**

NRLS nested structure:

1. Each stage game → non-linear solver, **specific to the model**
2. Combining stage game solutions to full game MPEs → **State Recursion algorithm**
3. Solving for all MPE equilibria → **Recursive Lexicographic Search**
4. Structural estimation → **Nested loop MLE with BnB on RLS tree**

**Performance** of NRLS

- ▶ Implementation of statistically efficient estimator (MLE)
- ▶ BnB with NRLS avoids full enumeration at no additional cost
- ▶ BnB augmented with non-parameteric likelihood bound gives sharper Bounding Rules → less computation larger samples
- ▶ **Computationally tractable**
- ▶ **Fully robust to multiplicity of equilibria**