Lecture 13: Review, Summary, and Potential Directions

Admin

Due end next week
- Quiz
- Homework
- Project

Let me know if you need an extension

No office hours next week
- Must be conducted virtually in the evening
- I should be around on Friday
- Or simply email me

Teaching feedback (please submit!)

Today's lecture

This class only touched the tip of the surface

- Modeling vs theory/algorithms

Hopefully, people outside of Game Theory have learnt something

- Originally meant to be a pure research seminar

We covered a broad range of topics (we'll review them in a moment)

An overview of what research topics I'm interested in

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An overview of what research topics I'm interested in

I'm **actively** looking for students (more later)

First: Any Questions For Quiz/Homework?

(Do on whiteboard)

Classic Material

Nash equilibrium in matrix games

- Definition, Best responses, existence via Brouwer/Kakutani
  - Refinements: Strong Nash equilibrium, Stable Nash equilibrium, Coalition Proof NE, Evolutionary Stable Strategies
  - Weakening: correlated equilibria, coarse CE, rationalizable strategy (players are BR-ing to some *beliefs* as to what opponents are doing)
- Limitations
  - PPAD-hard, inapproximable, hard to find →weak predictive power?
  - Need complete specification of game, payoffs, actions
  - Bounded rationality: Quantal response equilibria
- Algorithms
  - General-sum games
    - Vertex/Support enumeration, Nash as LCP, Lemke Howson (2 players) & path following, Integer programming (2 players) [Qn: what are some advantages/disadvantages?] Multiplayer general-sum game: homotopy methods: Govindan-Wilson, social welfare optimum equilibria, index of equilibria
  - Zero-sum games (next few lectures)
- Public libraries for game solving
  - gambit, NashPy
  - Most aren't super performant, but gets the job done

2-player zero-sum games

Minimax Theorem (important!)

- Conditions, Uses, Proof (many ways, e.g., Farkas Lemma, existence of no-regret methods)
- Extensions: Sions minimax theorem, Glicksberg theorem for continuous games (mathematically, not all have a value!), useful for market equilibria
- Equivalence to finding saddle-point

Importance of Exploitability (holds for general-sum games)

- Even if you are not into game solving, at least **evaluate** things properly
  - [Point out recent work in evaluation]
- Should evaluate based on worst case performance, BR of opponent
  - What makes a strong player? Beating noobs all the time or beating everyone by a small margin?
  - Non-transitivity in performance, A beats B, B beats C, C beats A
  - Example: Go players beat AlphaGo by exploiting oversights in AI (executed manually)
- In practice, difficult to evaluate exploitability for large games, but still an objective
- Alternatives to ELO scores that are based on equilibria (many others exist)
  - AlphaRank, Nash

Strategy spaces beyond simplexes: graphs, other constraints

Algorithms for solving 2p0s games

Linear programming + dualization

- Change min-max problem to min-min problem
  - Works on domains beyond the simplex too!

Decoupled methods

- Approximate equilibria, saddle point residual
- Fictitious play
- No-regret learning (outside of games)
  - Putting 2 no-regret agents against each other →converges in average iterate to Nash
    - Average iterate convergence vs Last iterate convergence. Best iterate convergence
    - Usually much faster (and space efficient) than LPs
  - Regret minimizers: RM, RM+, Hedge (+others, even projected gradient descent works)
    - Bandits (not full feedback, e.g., Exp3)
    - Relationship to optimization, in particular online mirror descent, e.g., Hedge = OMD with entropy DGF
    - Relationship to Blackwell approachability
    - Can be used to prove minimax theorem

Extensive Form Games

Definition, Game Trees

- Perfect information games, backward induction, subgame perfect nash equilibria, pure strategy equilibria, credible vs non-credible threats
- Imperfect information games
  - Information sets
    - Generalizes matrix games, Lying/bluffing/playing randomly
    - More “nice” structures: perfect recall, no-absent mindedness, timeability
  - Conversion to normal form strategies
  - Behavioral strategies
  - Sequence form (perfect recall), treeplexes

Algorithms

- General-sum: 2 players, Lemke’s algorithm, LCPs, integer programming
- Zero-sum games
  - Online learning, CFR, Scaled Extensions
- Meta-game algorithms: double oracle, PSRO

Other equilibria

Mediated equilibra

- Correlated equilibria, Coarse correlated equilibria
- Strong connections to no-regret learning, external regret vs. internal regret
- Poly-time in matrix games (LP or self-play), only very recently poly-time for EFGs (was open for a long time!)
- EFCE/EFCCE, Phi-regret, hindsight rationality

Stackelberg leadership

- Bi-level optimization: Usually super general and hard, but in certain cases can be solved efficiently using multiple LP method, poly-time algorithms, in EFG is NP-hard (Conitzer & Sandholm) apart from 1-2 special cases (perfect info without chance)

Some applications of both

- Security, Battleship, Social welfare optimal strategies

Some other “rare” equilibria, e.g., Nash Stackelberg equilibria

Markov Games

Generalization of MDPs

- POMDPs would be POSGs (very hard to scale in practice)

Difference with EFGs

- Trajectories with cycles exist

Centralized method

- Minimax-Q learning (very, very old)

Decentralized methods

- V-learning (CE, CCE, NE for 2p0s)

Deep learning-based methods

- MADDPG + many, many others
- Check out Stefano Albrecht’s textbook for a reasonable coalition

Other topics

Learning Dynamics and Games

- Hedge, ”energy” conservation, Euler discretization, difference between continuous dynamics/EGT and discrete variants
- Last iterate convergence, RVU bounds

Subgame solving

- Value function at a node level does **not** exist in IIEFG
- Need value ”functional” sometimes, value depends on what opponent strategy chooses. Key difference between multiplayer and single player, e.g., POMDP has belief state space and belief-values
- Extend method in chess (roughly) to IIEFG
  - What makes a good value in practice? E.g., darkchess → use perfect information value?
- Safe subgame solving, Max-margin solving (other methods: ReBel, reach subgame solving, DeepStack), compatibility with deep learning based methods
- Extension to general-sum games, set of achievable payoffs

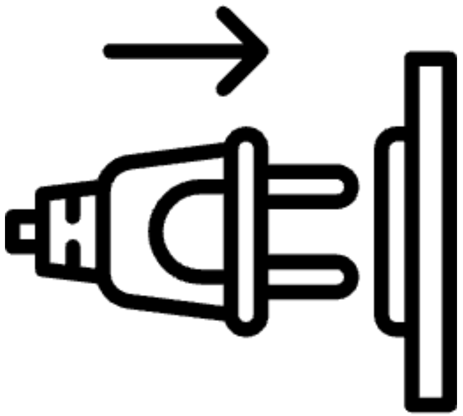
My interests and thoughts

What I’m interested in

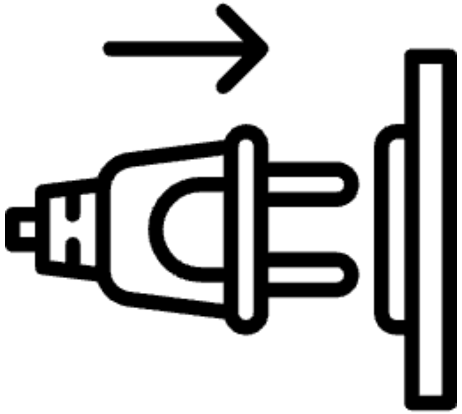
… because everyone has their own agenda

"So far the field has struggled to take techniques like this *out of the laboratory and game environments and into the real world…"*

-Gary Marcus on Alphastar, 2019



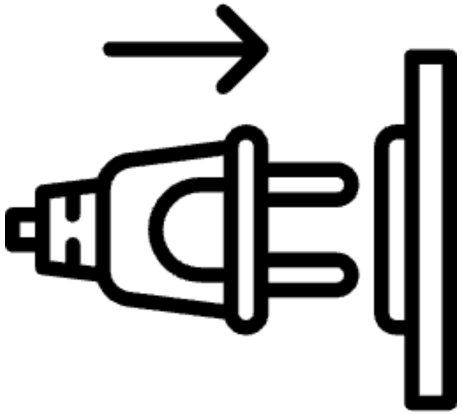
Game Theory in the real-world



Game Theory in the real-world

Traditional

More modern



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More modern

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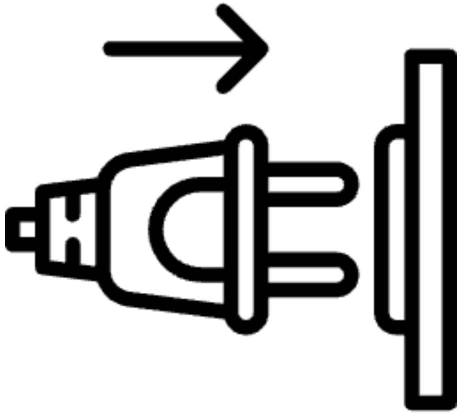

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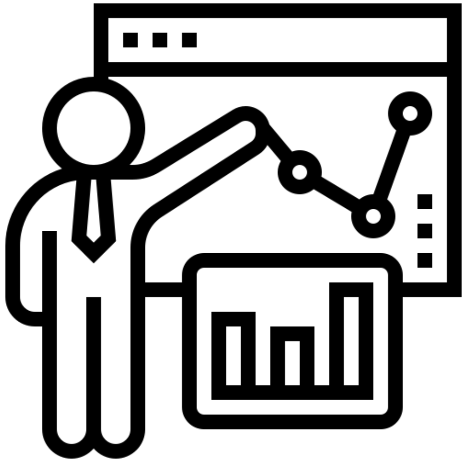
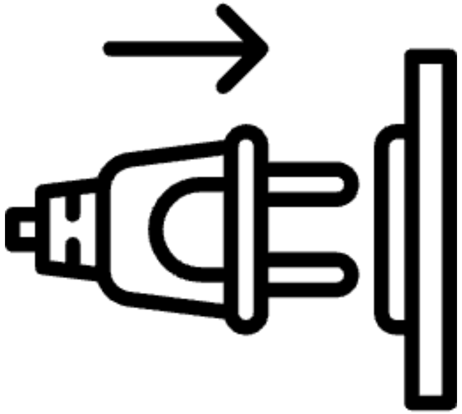


2. Interpretability & sensemaking



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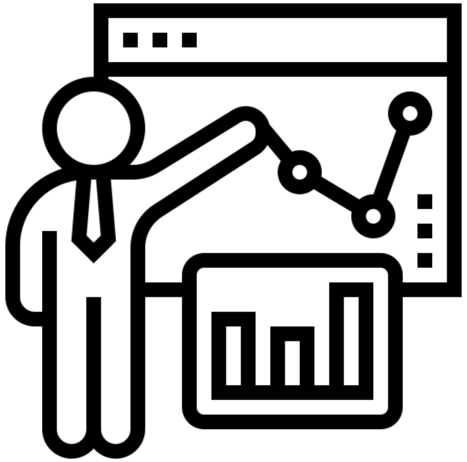


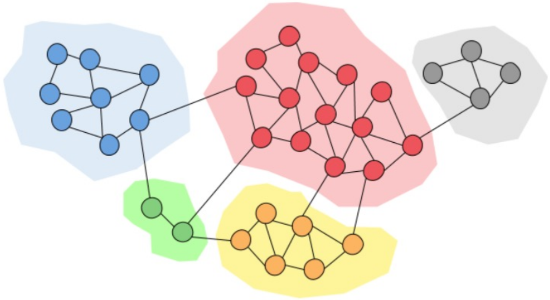
2. Interpretability & sensemaking

3. Challenging assumptions

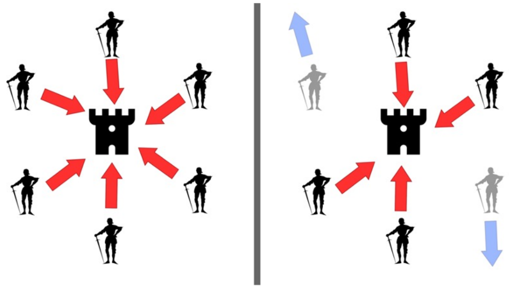
Direction 1: Algorithms & Structure

Real world problems are tough (large) but have lots of structure!

Ridesharing



Social media analysis



Distributed systems

Logistics

Cybersecurity

Politics

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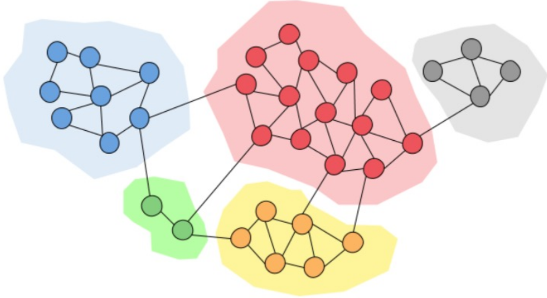

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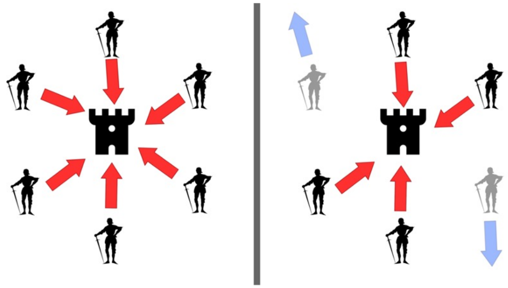

Distributed systems

Logistics

Cybersecurity

Politics

- Multiplayer, team games
- General-sum
- Imperfect information
- Jointly continuous & discrete
- Huge, combinatorial structure

How do we **model** real-world scenarios?

- Applications
  - Logistics and Patrolling
  - Cyber and network security
- Equilibrium concepts
  - Multi-defender security games
  - Extensive-form correlated equilibria
  - Sparse equilibrium

How do we **solve** these games we have defined?

- Machine learning
  - Function approximation for general-sum game solving
- Optimization
  - Differentiable game solvers (in EFGs)
  - Variants of double oracle/PSRO/iterative strategy generation
  - Variants of self-play + regret minimization
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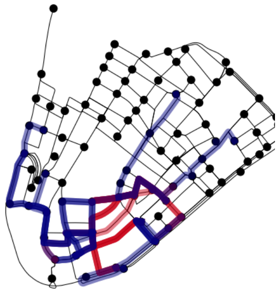

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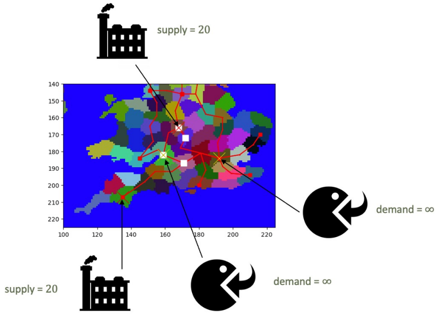

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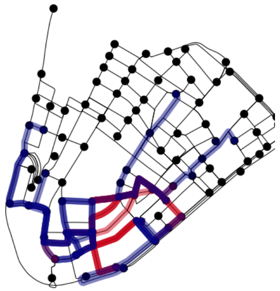

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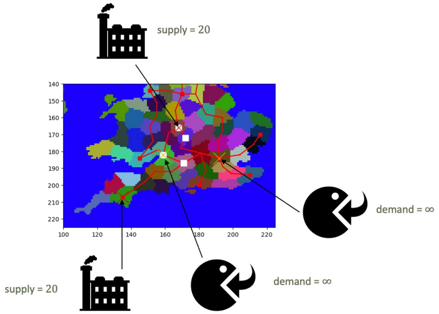

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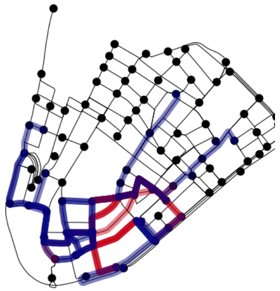

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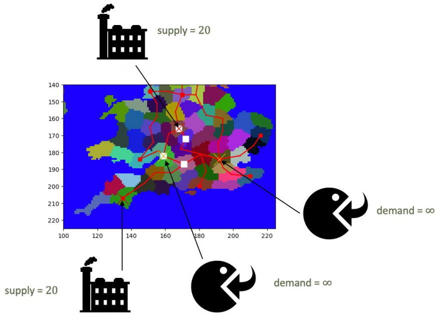

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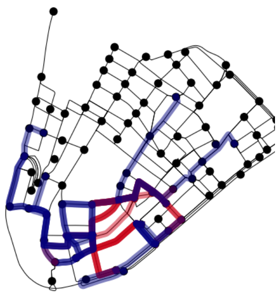

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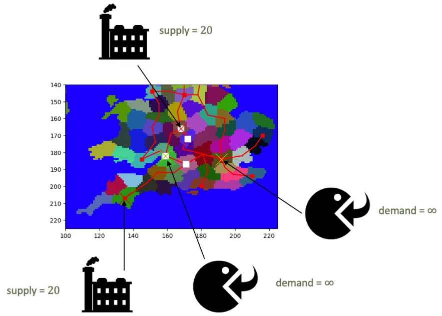

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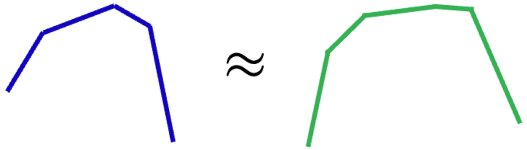

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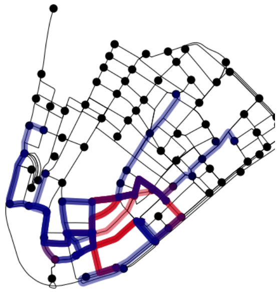

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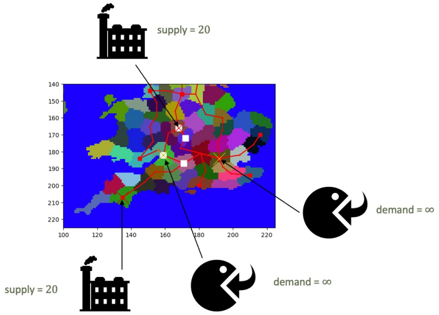

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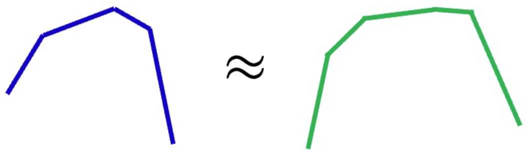

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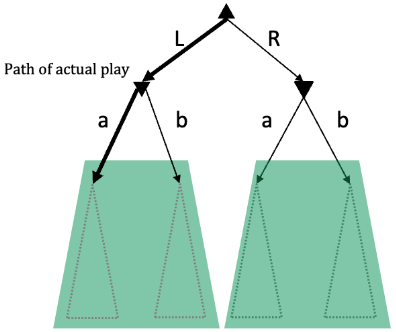

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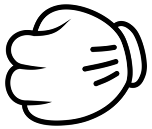
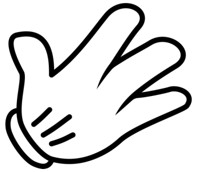
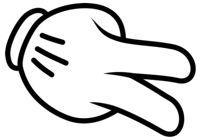
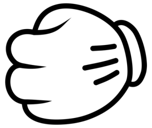
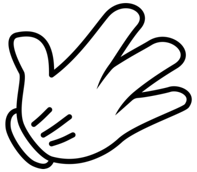
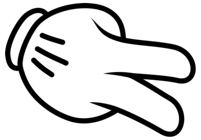
Inverse Game Theory

Learning player utilities from their past actions played in games

			
	0	$-b_1(x)$	$b_2(x)$
	$b_1(x)$	0	$-b_3(x)$
	$-b_2(x)$	$b_3(x)$	0

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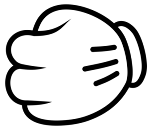
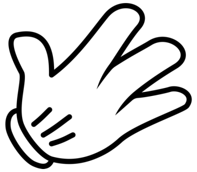
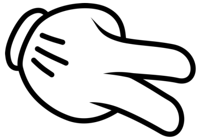
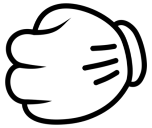
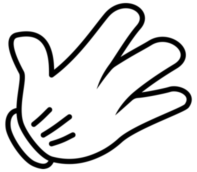
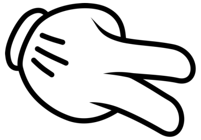
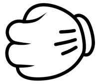
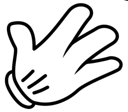
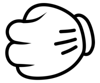
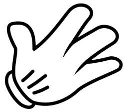
			
	0	$-b_1(x)$	$b_2(x)$
	$b_1(x)$	0	$-b_3(x)$
	$-b_2(x)$	$b_3(x)$	0

Learn

i.i.d samples from equilibrium strategies

$a^{(1)} =($ , $)$

$a^{(2)} =($ , $)$

$a^{(3)} =($ , $)$

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Side Information

$$x^{(1)} = [0.1, 0.5]$$

$$x^{(2)} = [0.3, 0.7]$$

$$x^{(3)} = [0.9\ 0.2]$$

...

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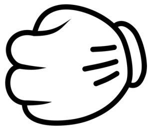
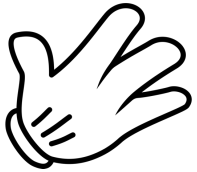
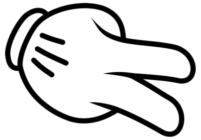
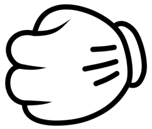
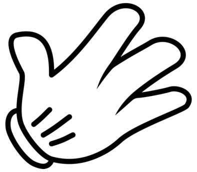
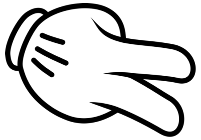
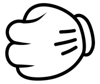
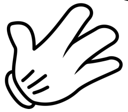
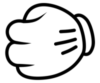
Learning player utilities from their past actions played in games

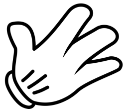
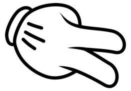
			
	0	$-b_1(x)$	$b_2(x)$
	$b_1(x)$	0	$-b_3(x)$
	$-b_2(x)$	$b_3(x)$	0

Learn

i.i.d samples from equilibrium strategies

$a^{(1)}=($  ,  $)$

$a^{(2)}=($  ,  $)$

$a^{(3)}=($  ,  $)$

…

Side Information

$$x^{(1)}=[0.1, 0.5]$$

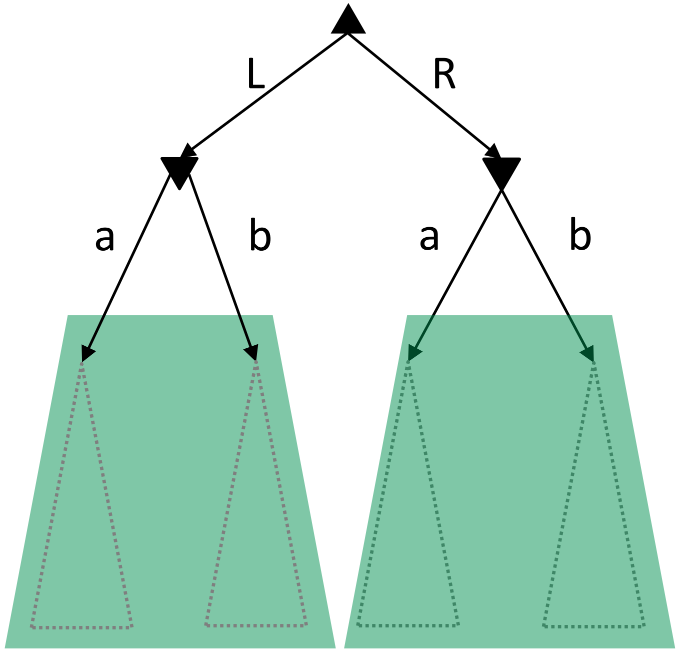
$$x^{(2)}=[0.3, 0.7]$$

$$x^{(3)}=[0.9\ 0.2]$$

…

- Utilities are *functions* of side information x
  - E.g., utilities depend on age, demographic of players

Subgame Resolving



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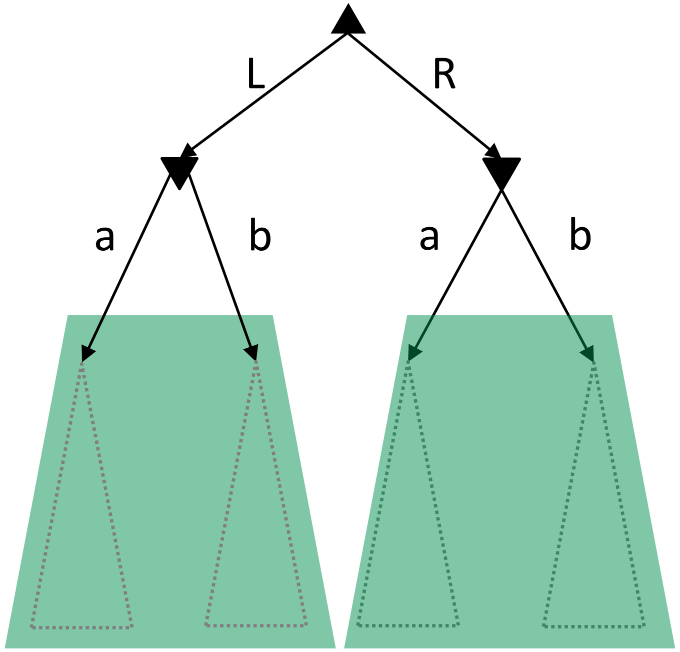
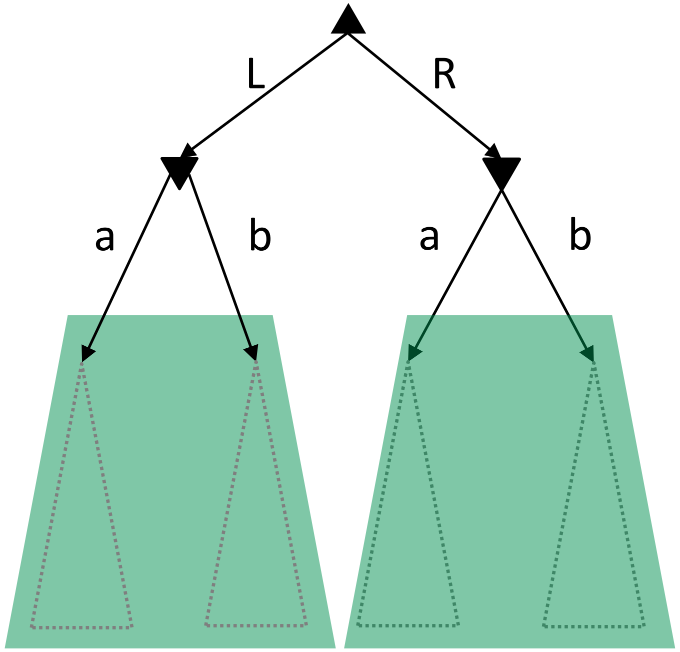


Consider Chess

- Resolving is only initiated from states faced in **actual play**
- Avoid search from states which we've never reached

Subgame Resolving



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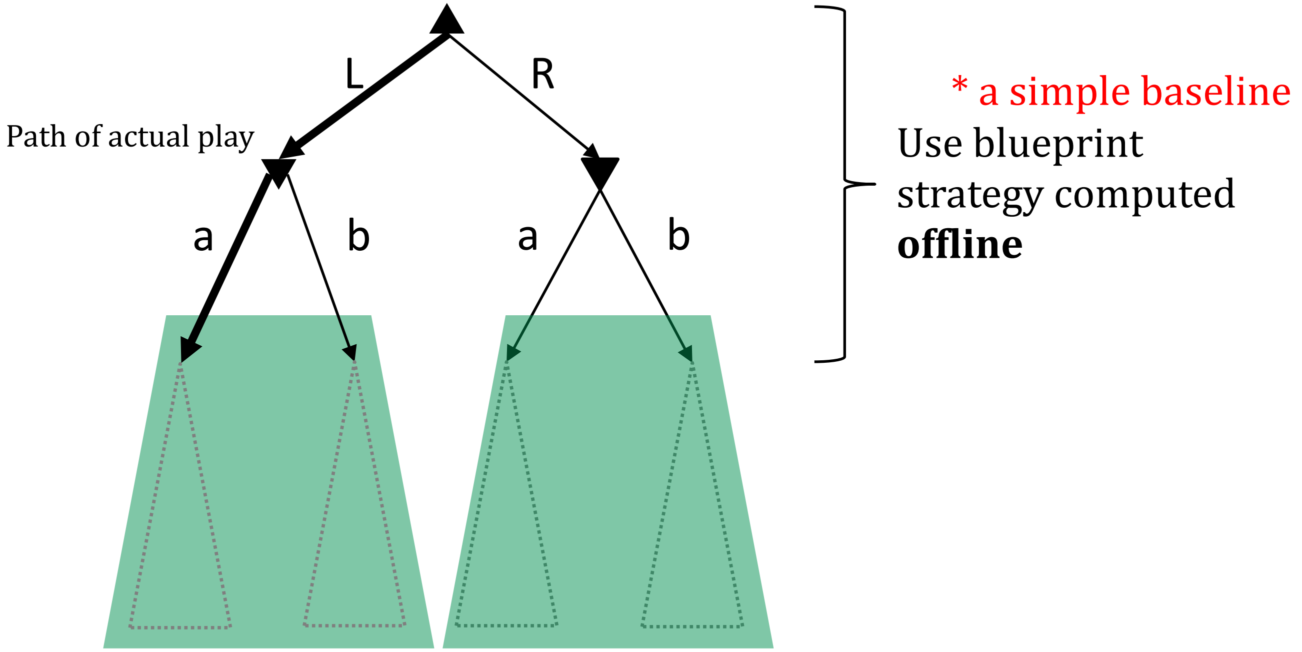
Extensions to zero-sum imperfect information games

- Crucial component of top poker bots (Deepstack, Libratus)
- Us: Can be extended to various general-sum games safely!

Subgame Resolving



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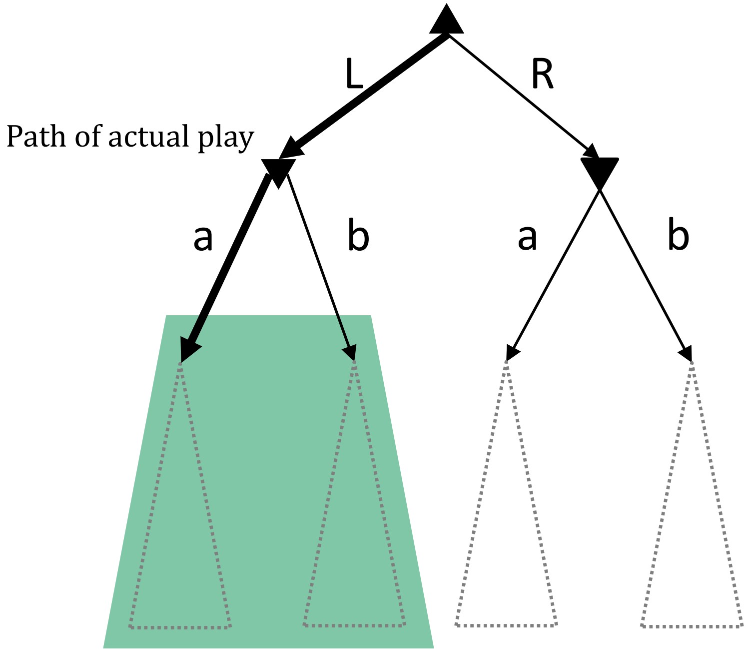

* a simple baseline

Use blueprint strategy computed **offline**

Compute refined strategy **online** *only for subgame entered*

Consider Chess

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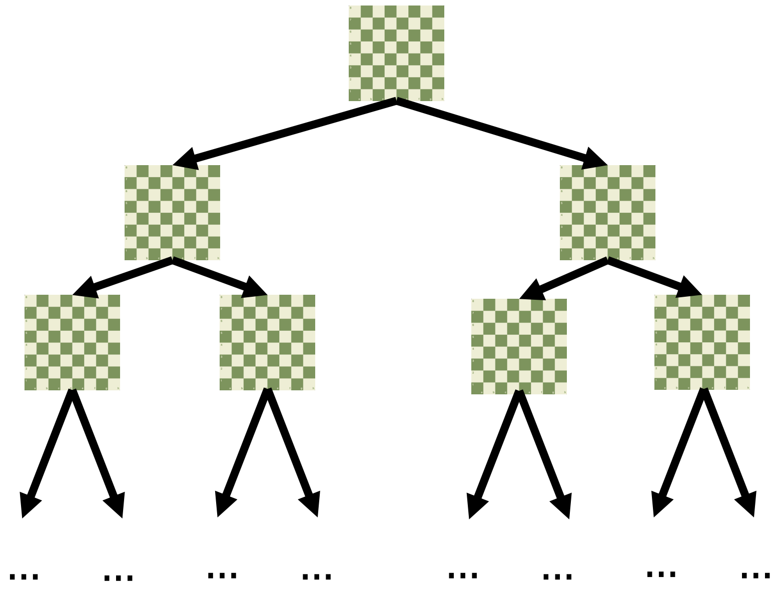
Extensions to zero-sum imperfect information games

- Crucial component of top poker bots (Deepstack, Libratus)
- Us: Can be extended to various general-sum games safely!

Resolving will do at least as well as the blueprint!

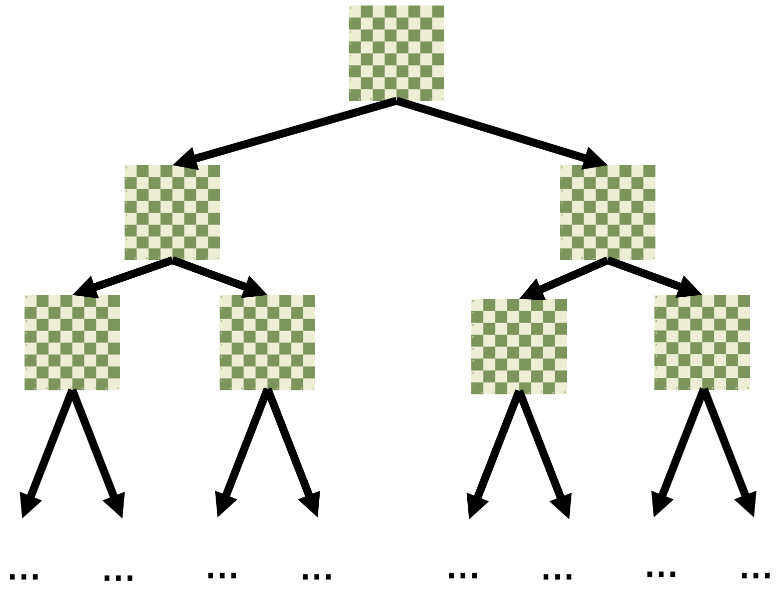
Game Solving with Function Approximation



Game Solving with Function Approximation

Consider zero-sum games

- Game tree too large to traverse explicitly
- **Value Function** $V(s)$ approximates how "good or bad" each state is



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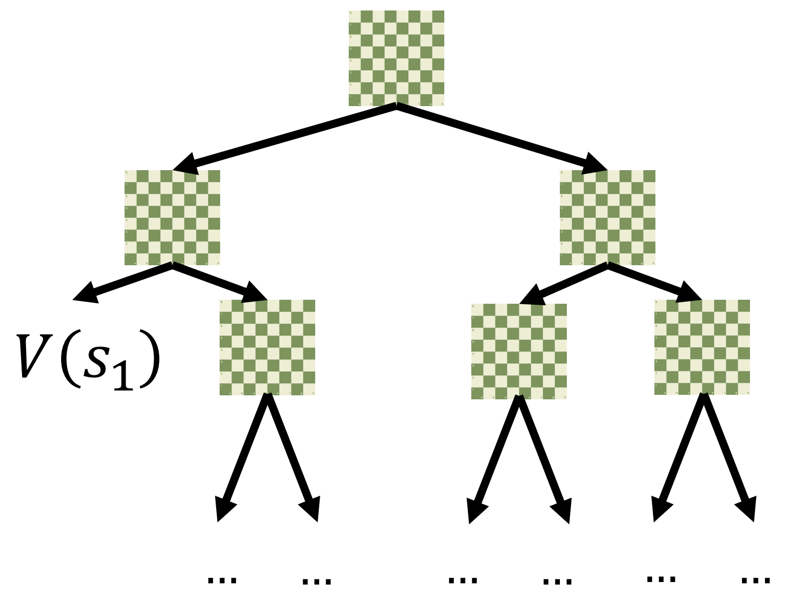

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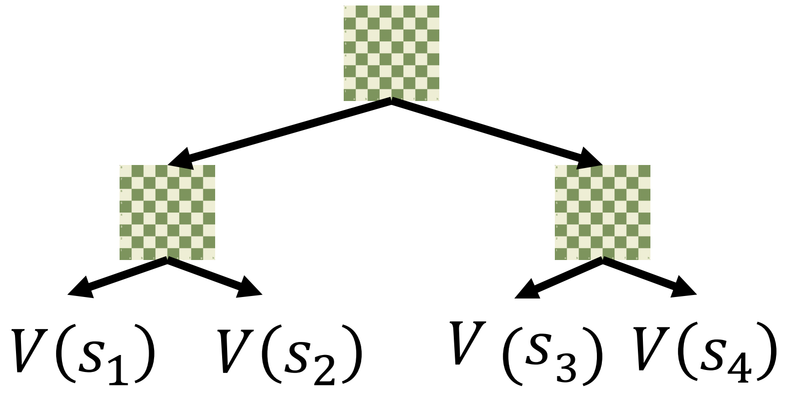

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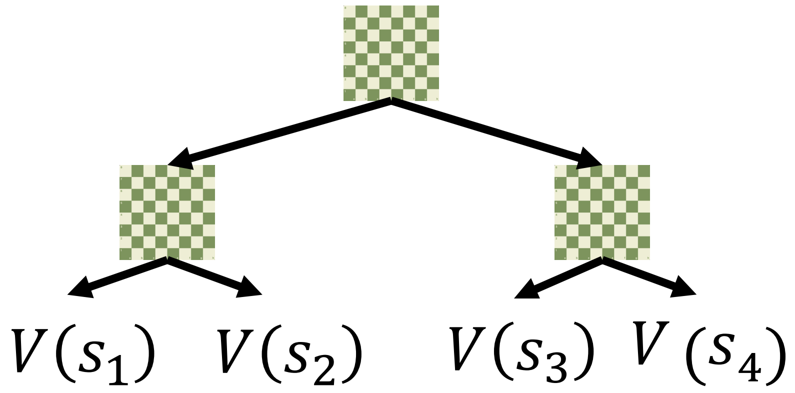
Previously (e.g., Deep Blue)

- Handcrafted evaluation function $V(s)$ based on heuristics from experts



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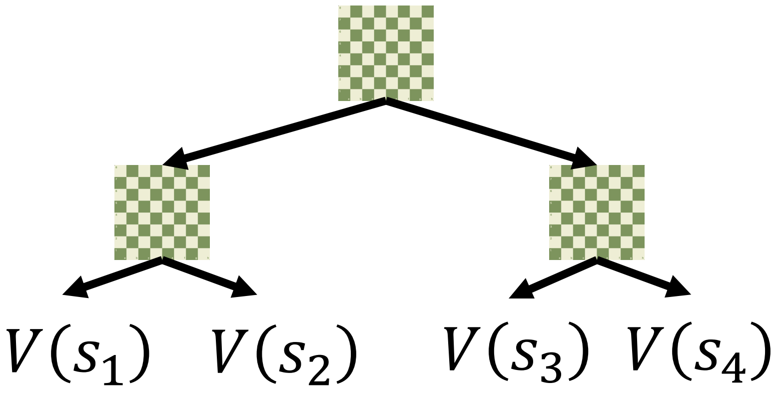
- $V_\phi(s)$ is a network parameterized by ϕ approximating the value of s



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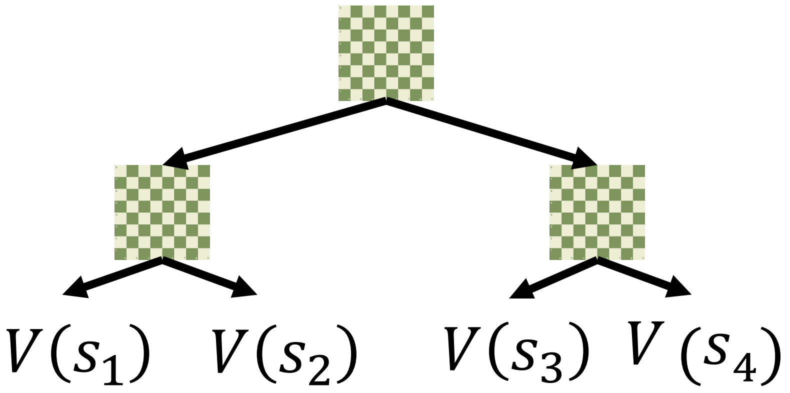

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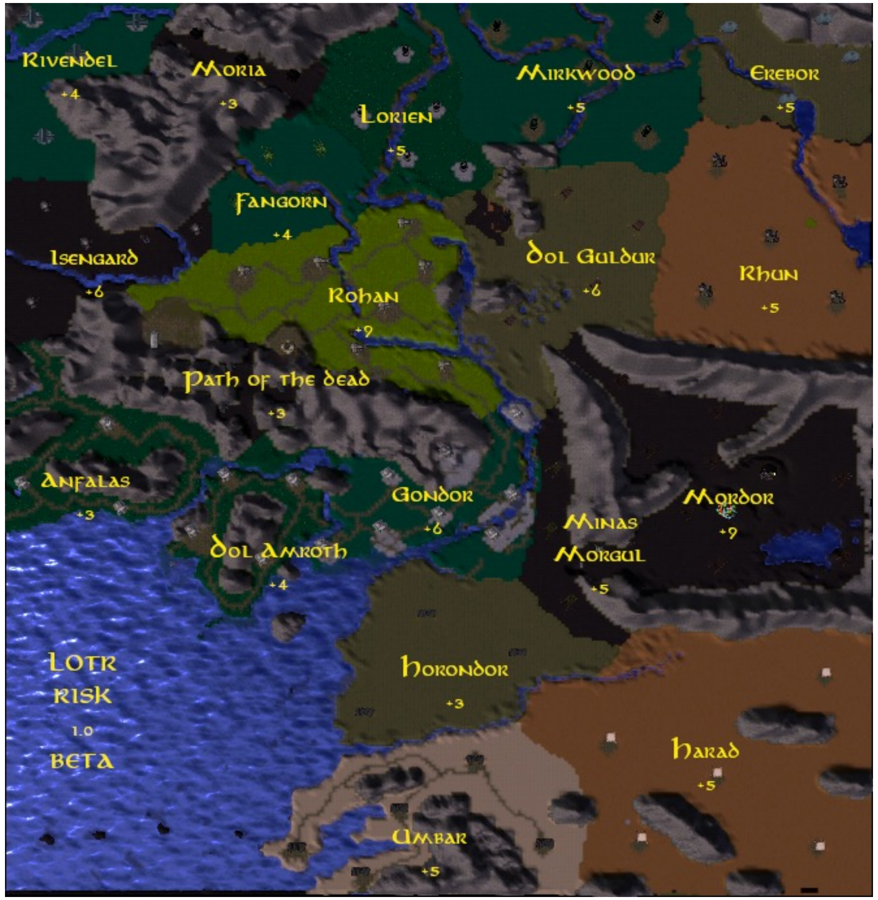
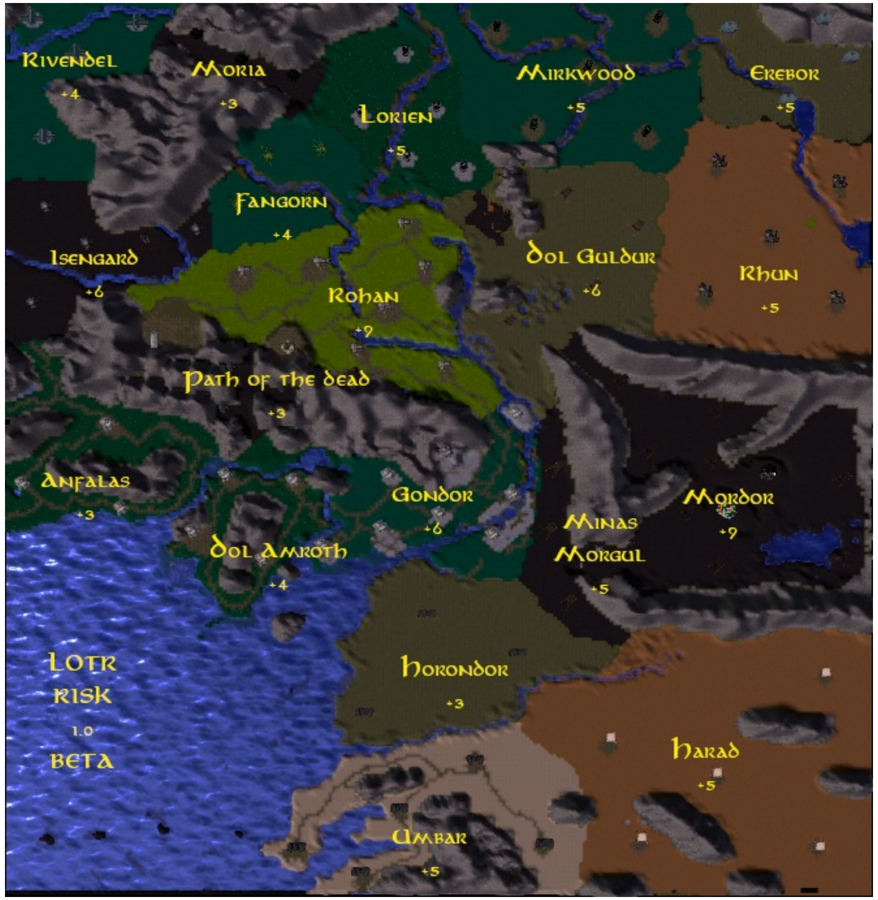
Also applies to general sum (Stackelberg) games in a principled manner!

Need to predicting **achievable sets** of payoffs, "value" of vertex is not just a scalar or fixed size vector

Multidefender Security Games



Multidefender Security Games

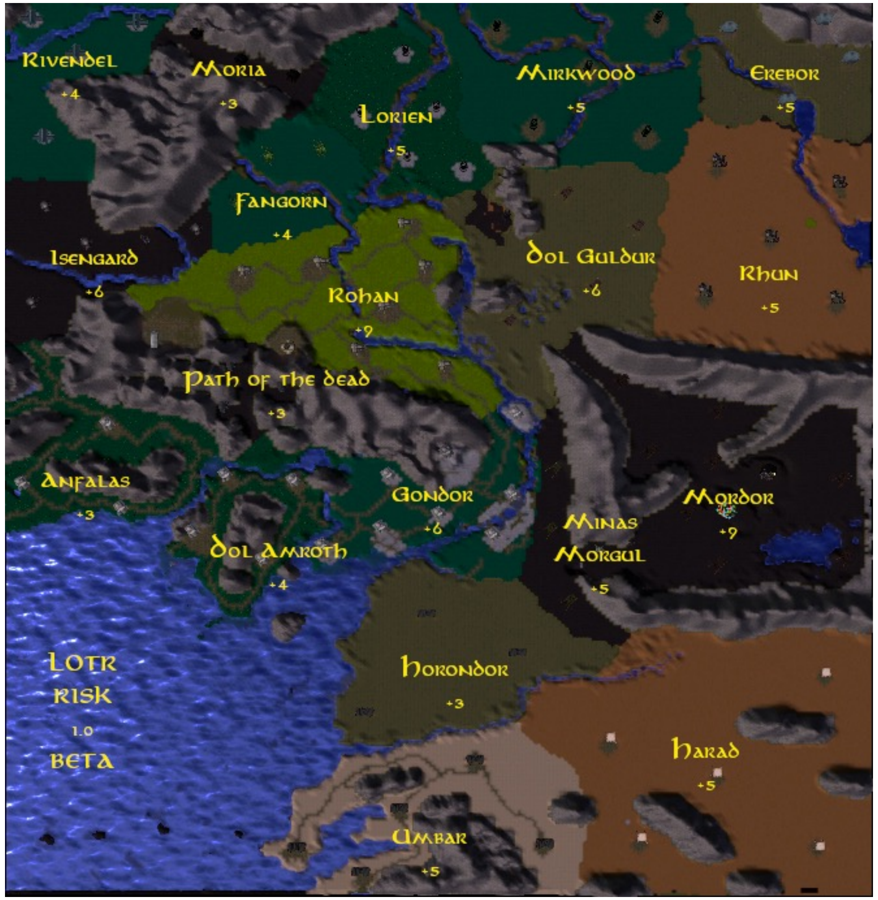


attacker

v.s.

defender**s**

Multidefender Security Games



v.s.

attacker

defender**s**

Defenders *each* choose how to distribute their armies. Orcs choose a target to attack.

Multidefender Security Games

v.s.

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Heterogenous defenders

Multidefender Security Games

v.s.



attacker

defenders

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Heterogenous defenders	Defensive Schedules

Multidefender Security Games

v.s.

attacker

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Heterogenous defenders

Defensive Schedules

Is there a "stable" allocation of defensive resources?

Not always but yes, under some assumptions.

Multidefender Security Games

attacker

v.s.

defenders

Defenders *each* choose how to distribute their armies. Orcs choose a target to attack.

Heterogenous defenders

Defensive Schedules

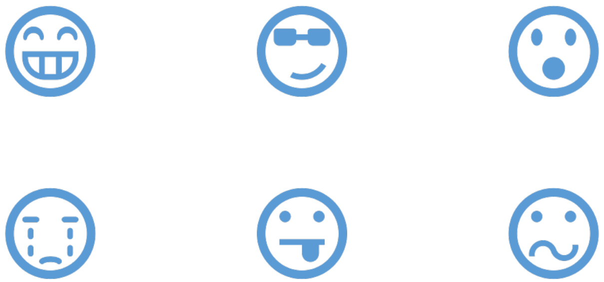
Is there a “stable” allocation of defensive resources?

Not always but yes, under some assumptions.

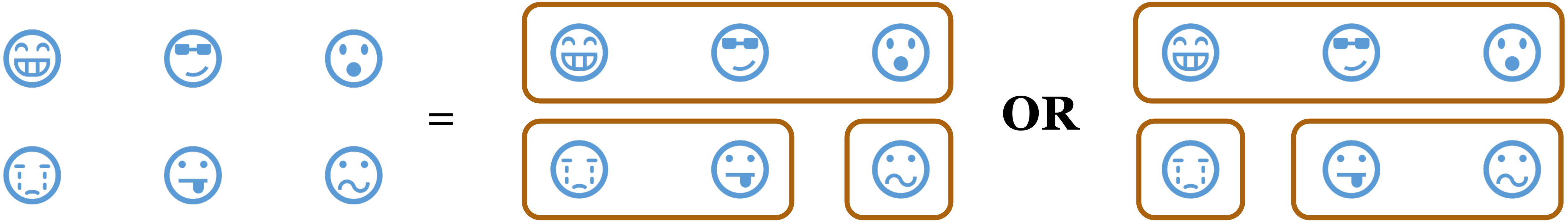
~~Democracy is two wolves and a sheep voting on whats for dinner.~~

Democracy is two or more sheet deciding who to throw to the wolves.

Coalition Structure Learning



Coalition Structure Learning



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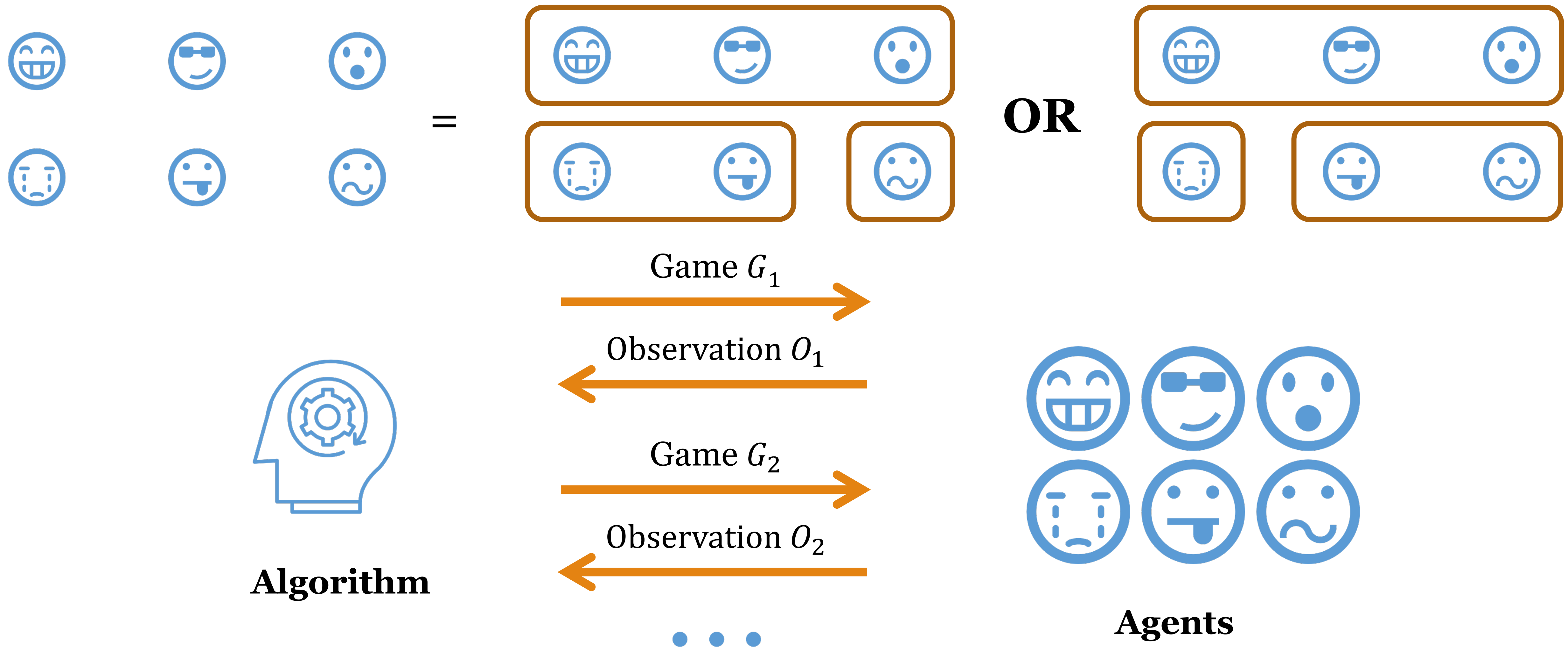

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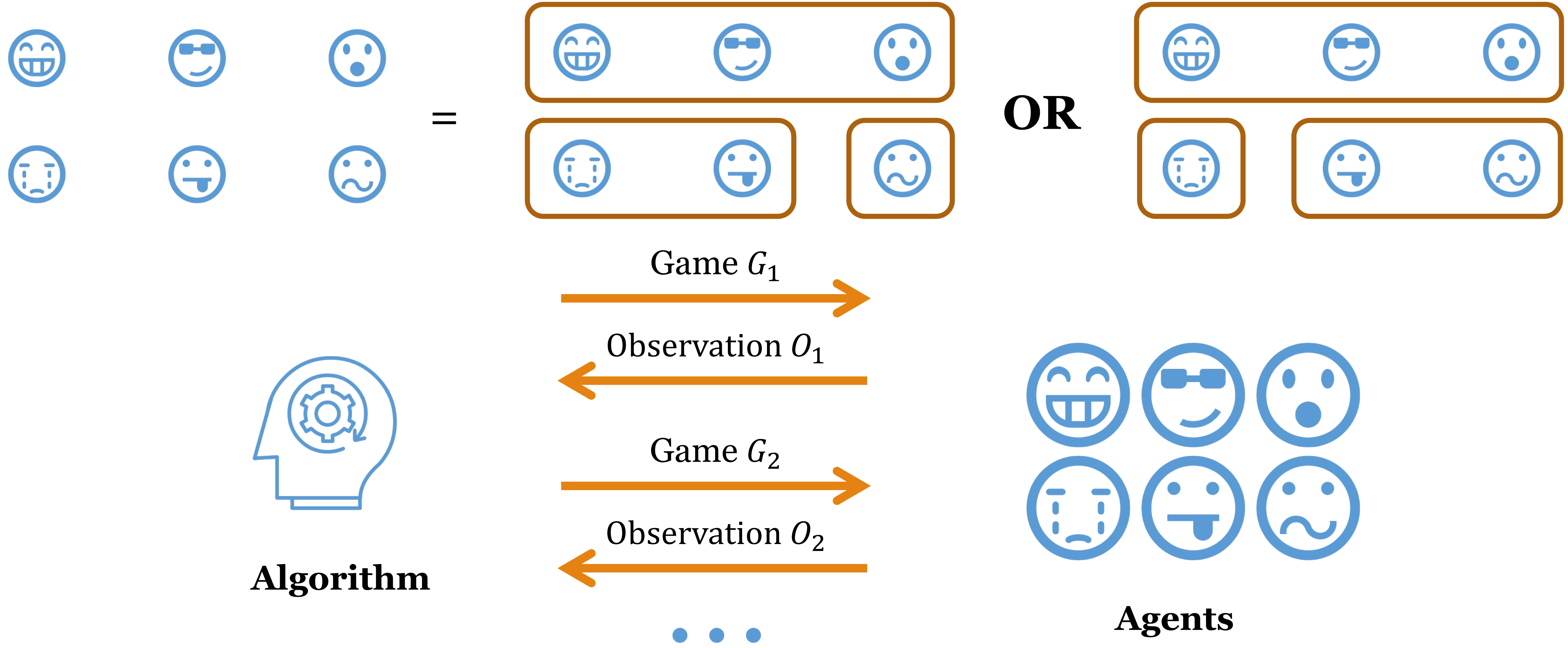
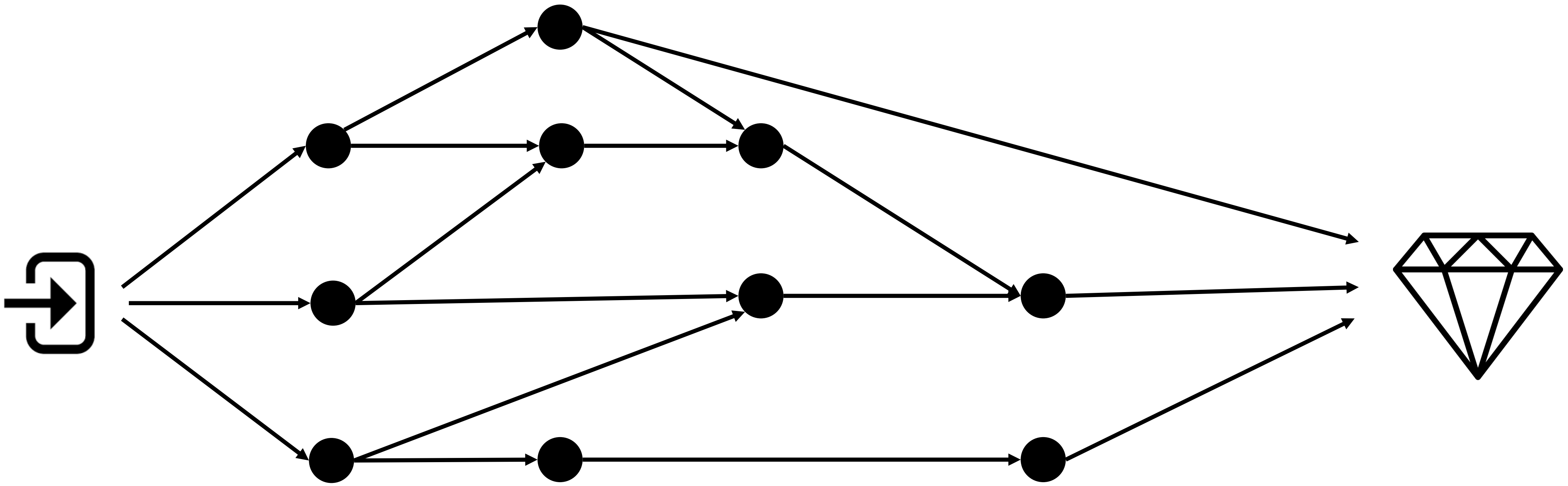


Discovers true optimal in smallest number of tests!

Example: Network Protection Game

*Abstracted and super simplified



Nodes: Machines, servers, routers

Edges: Potential vulnerabilities

Example: Network Protection Game

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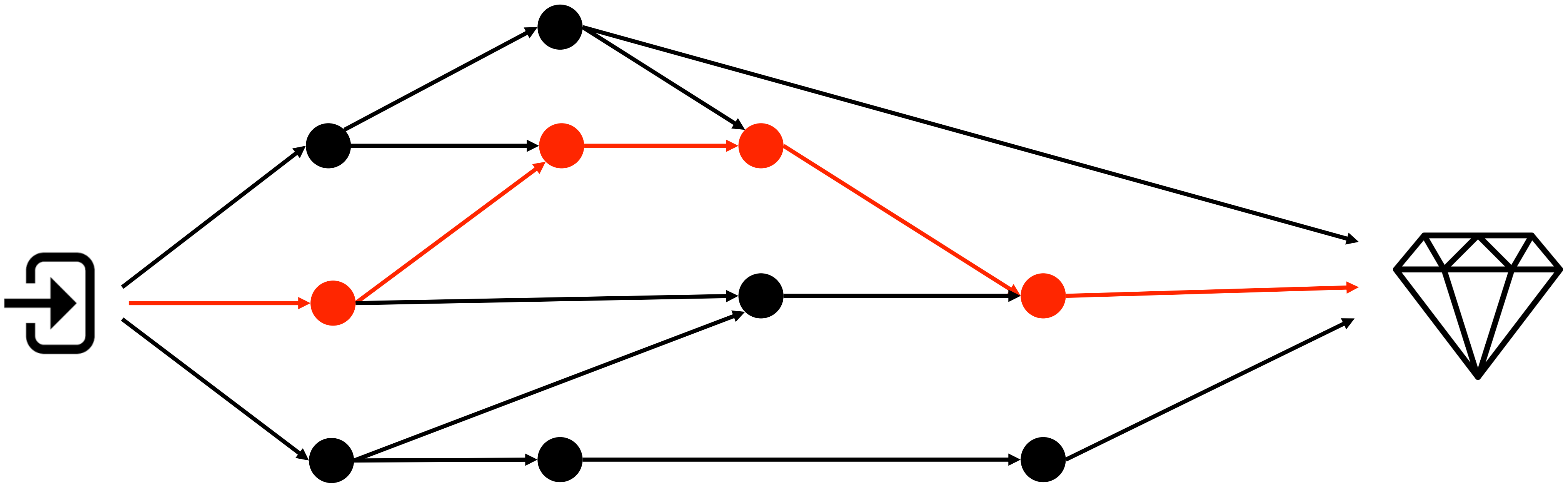

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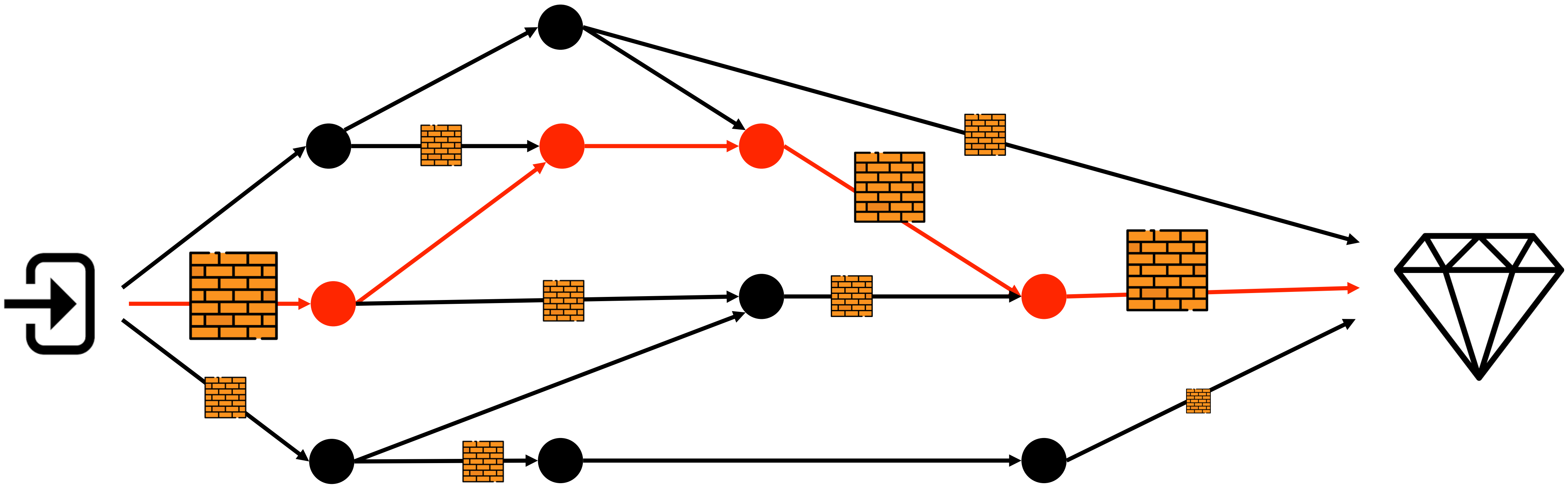

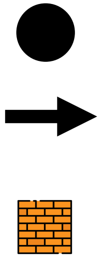

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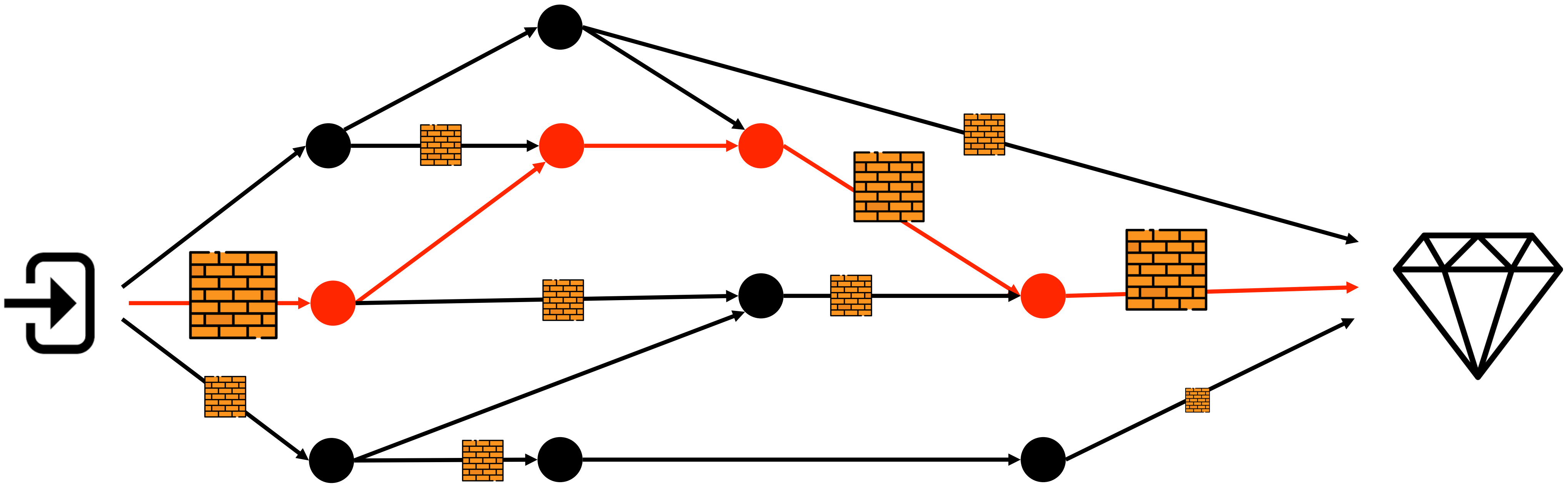
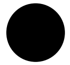
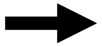


 Nodes: Machines, servers, routers

 Edges: Potential vulnerabilities

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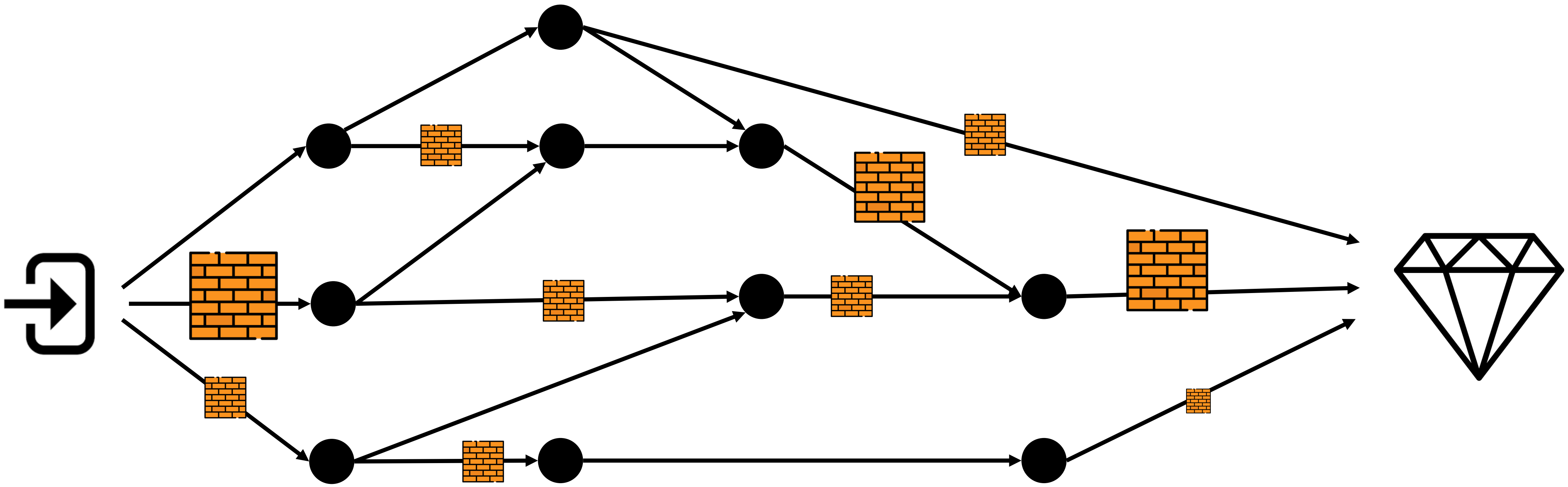
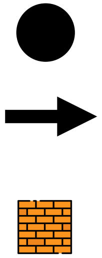
Reduces to a longest shortest path problem

(super easy for simple constraints, easily scale to around tens of millions of nodes)

Pivoting: Intruder is not stupid!

https://lingchunkai.github.io/pdf/AICS-2025.pdf





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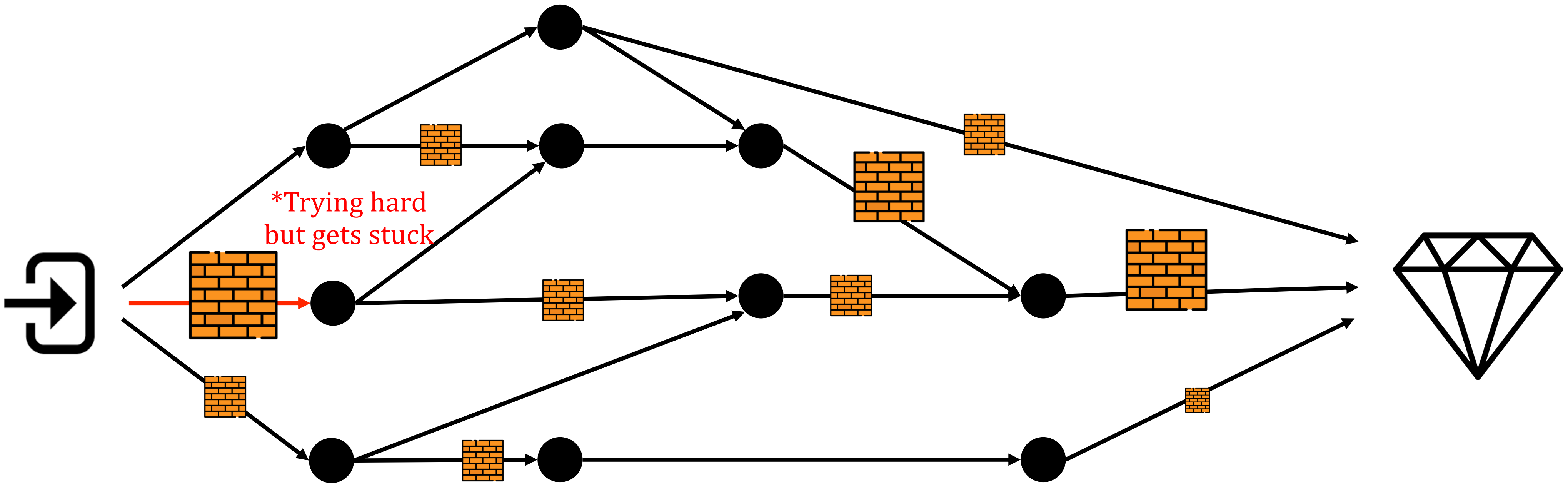

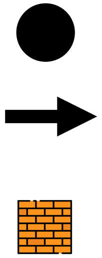

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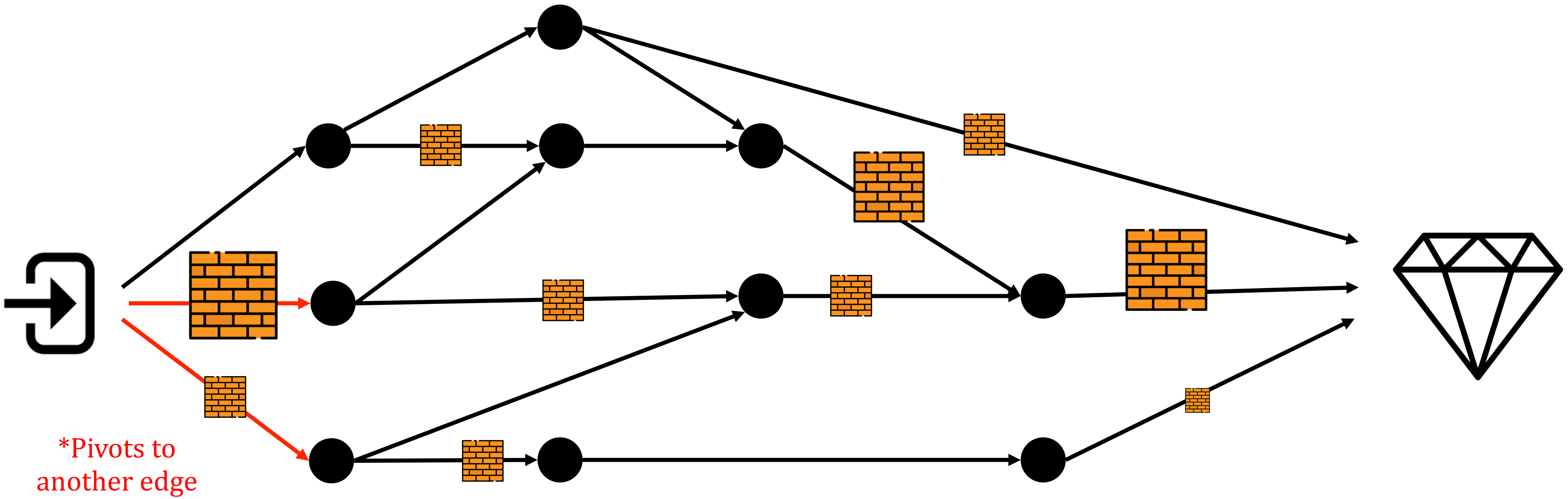

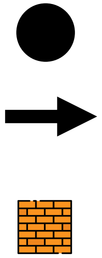

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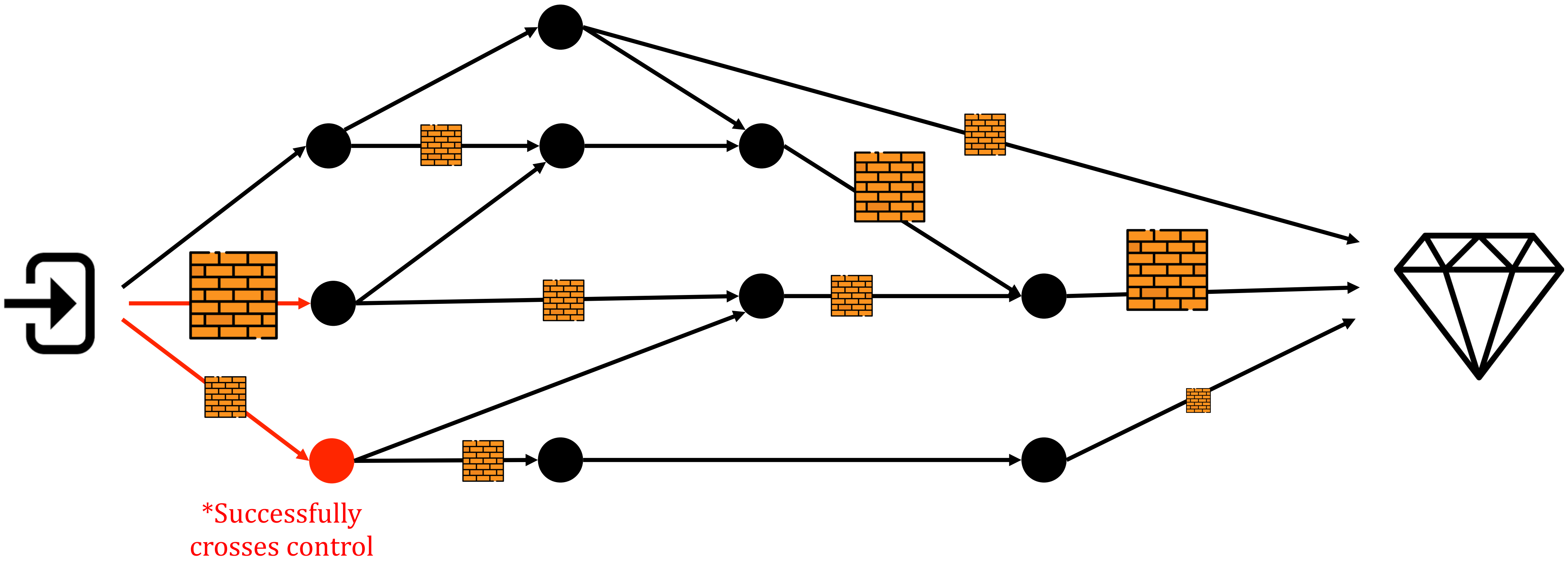

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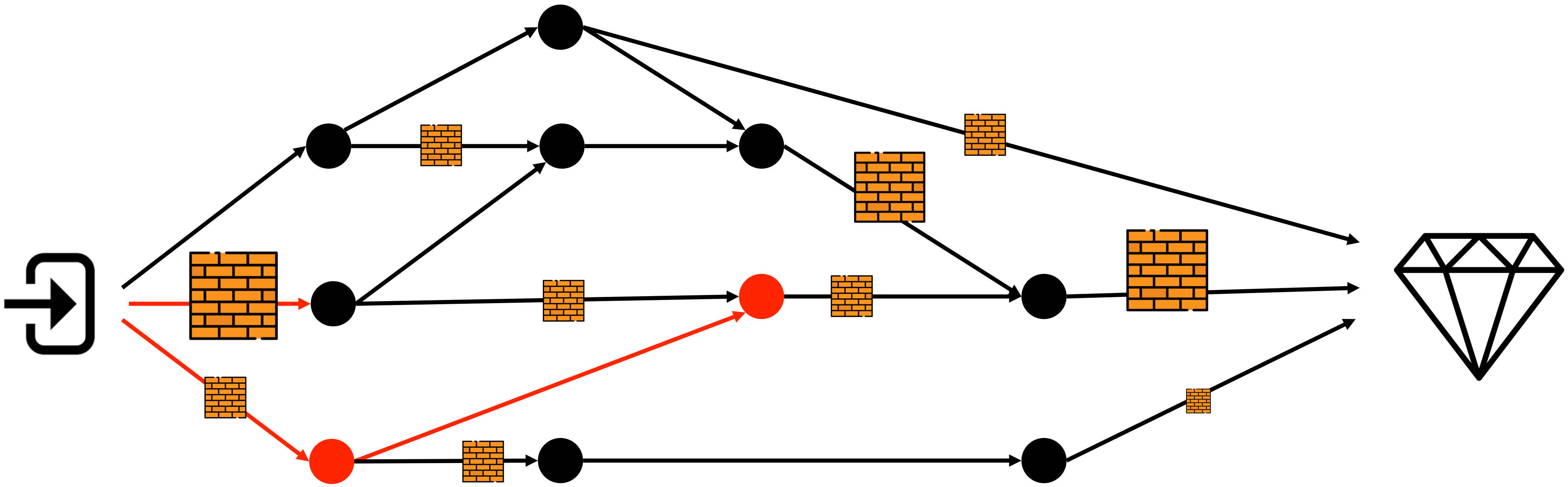

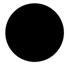

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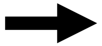

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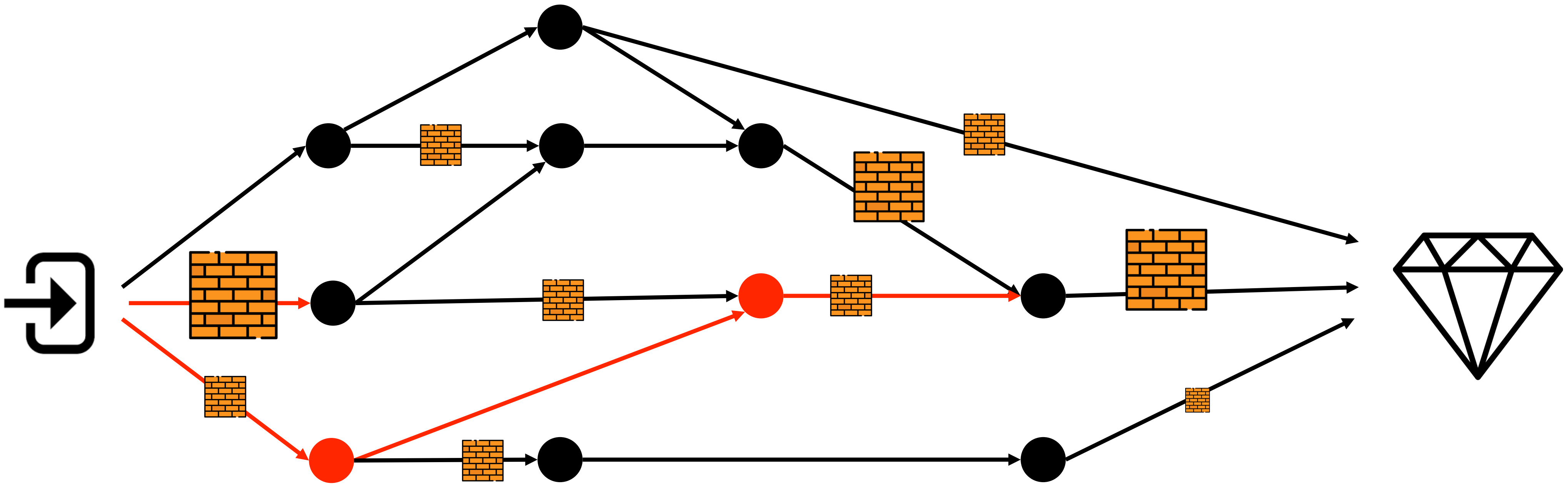

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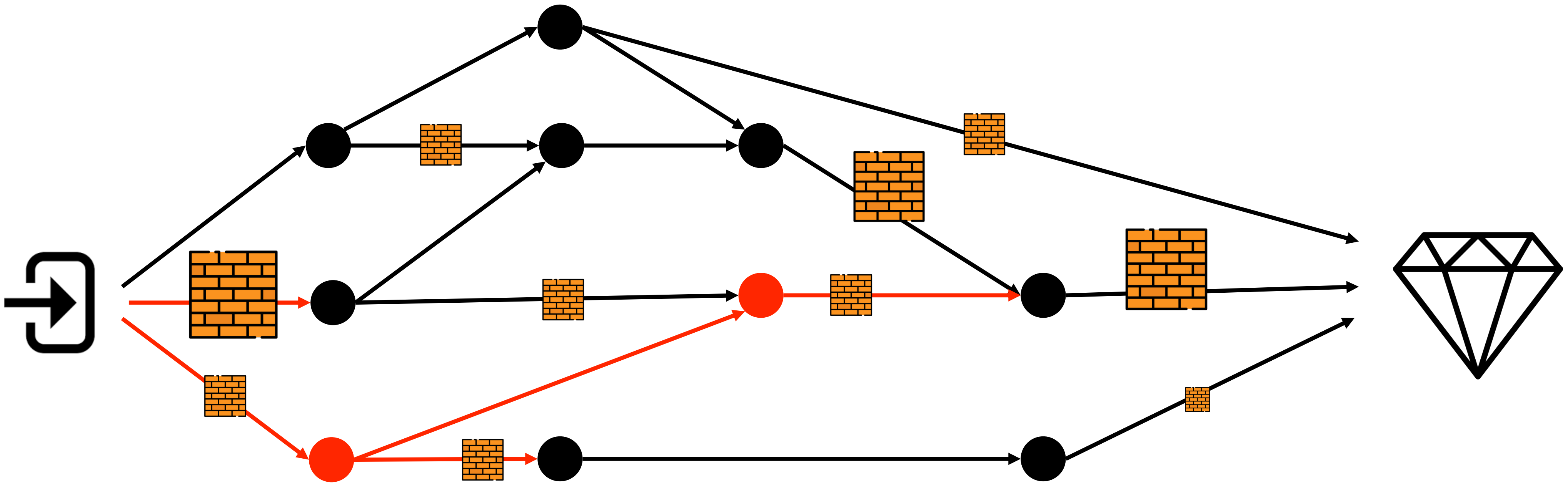

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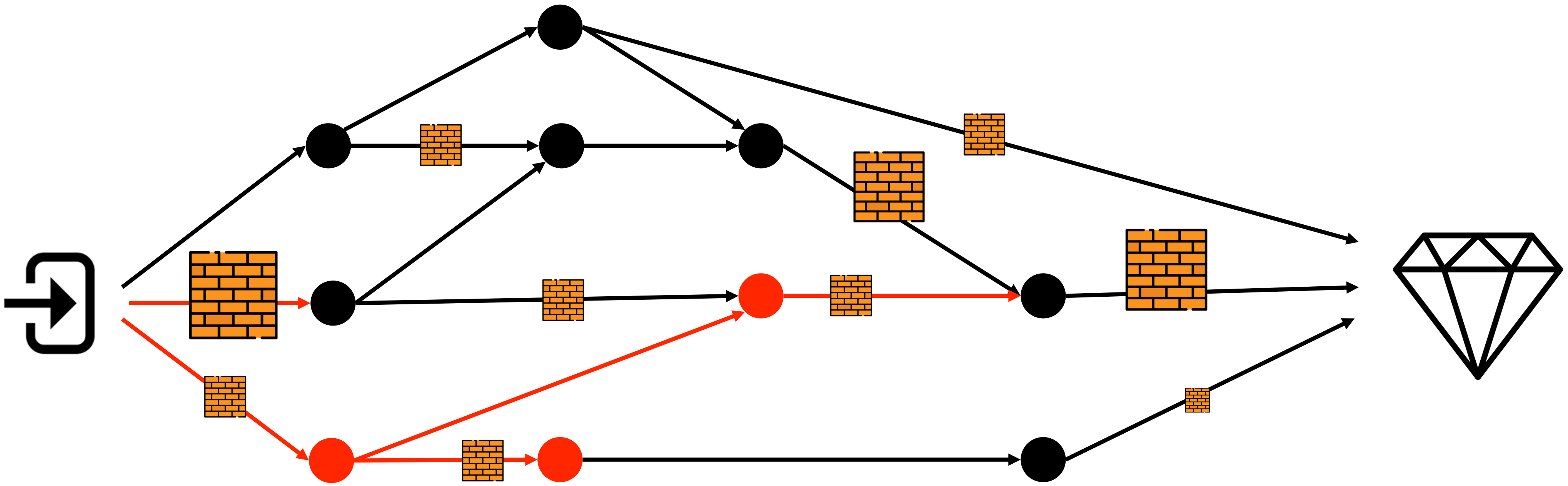

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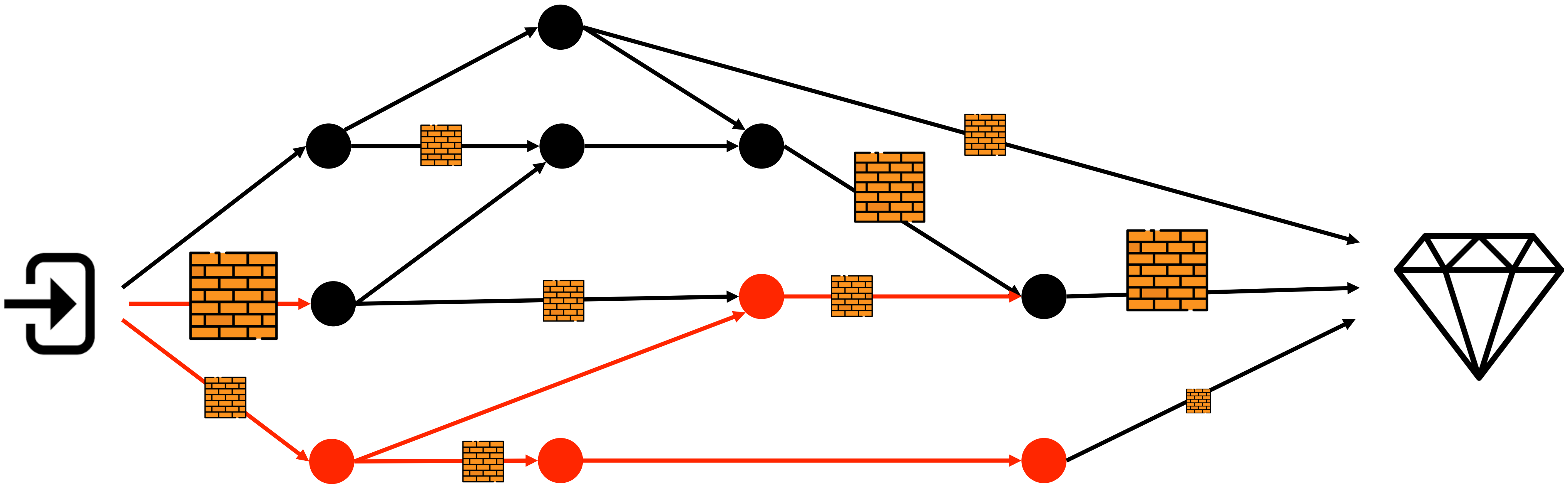

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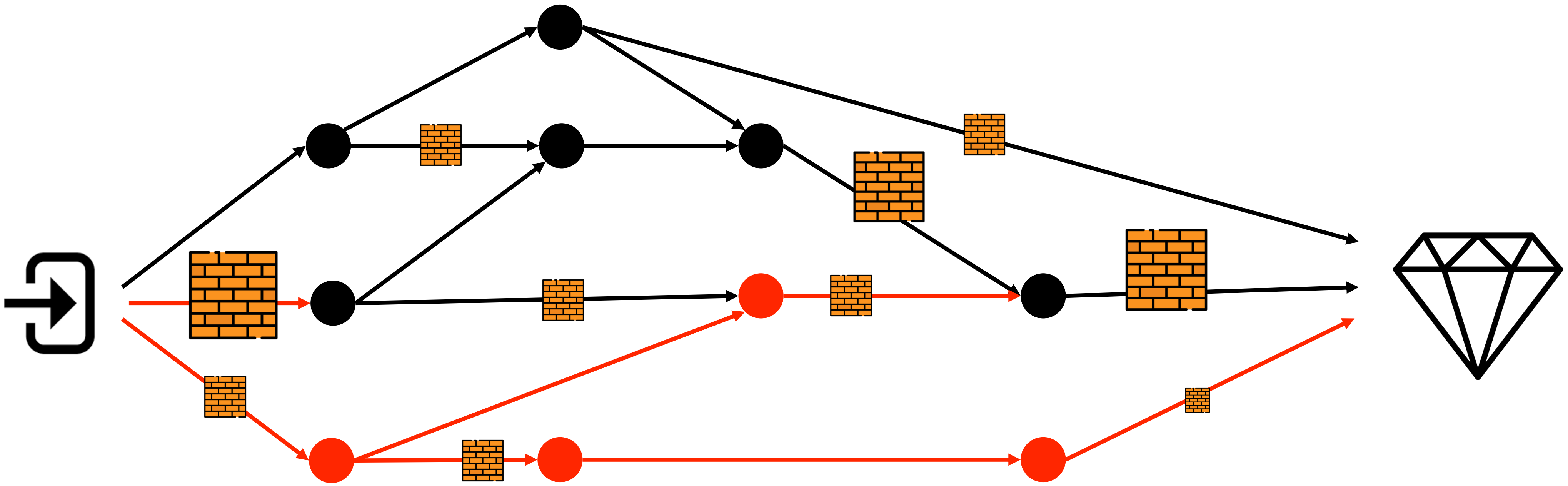

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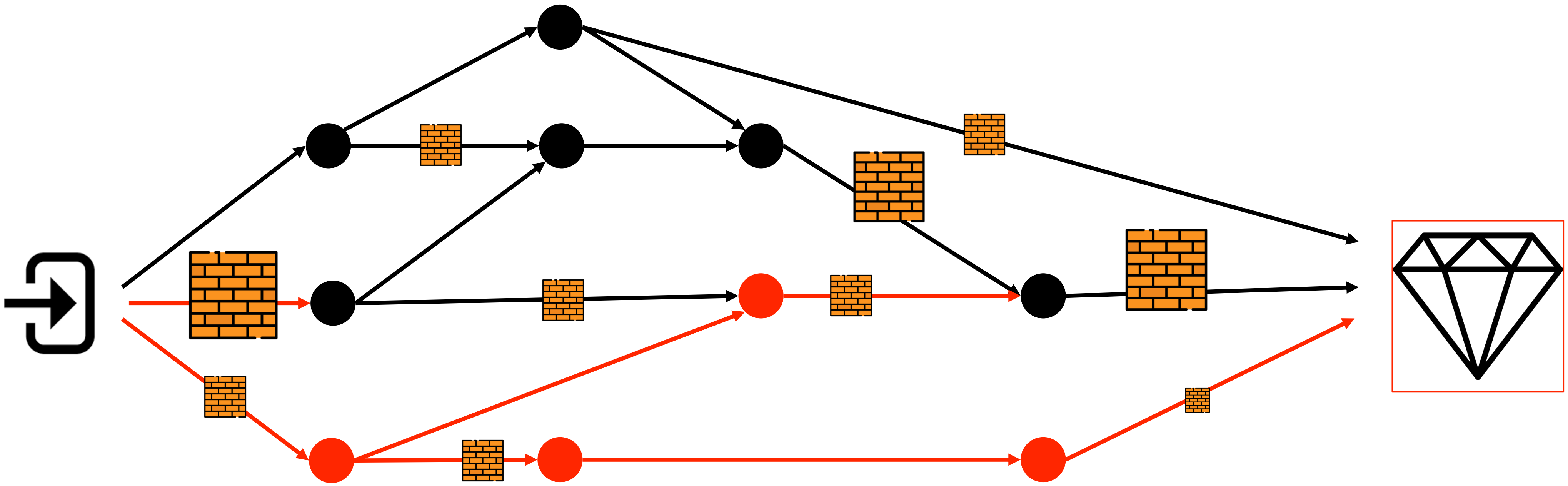

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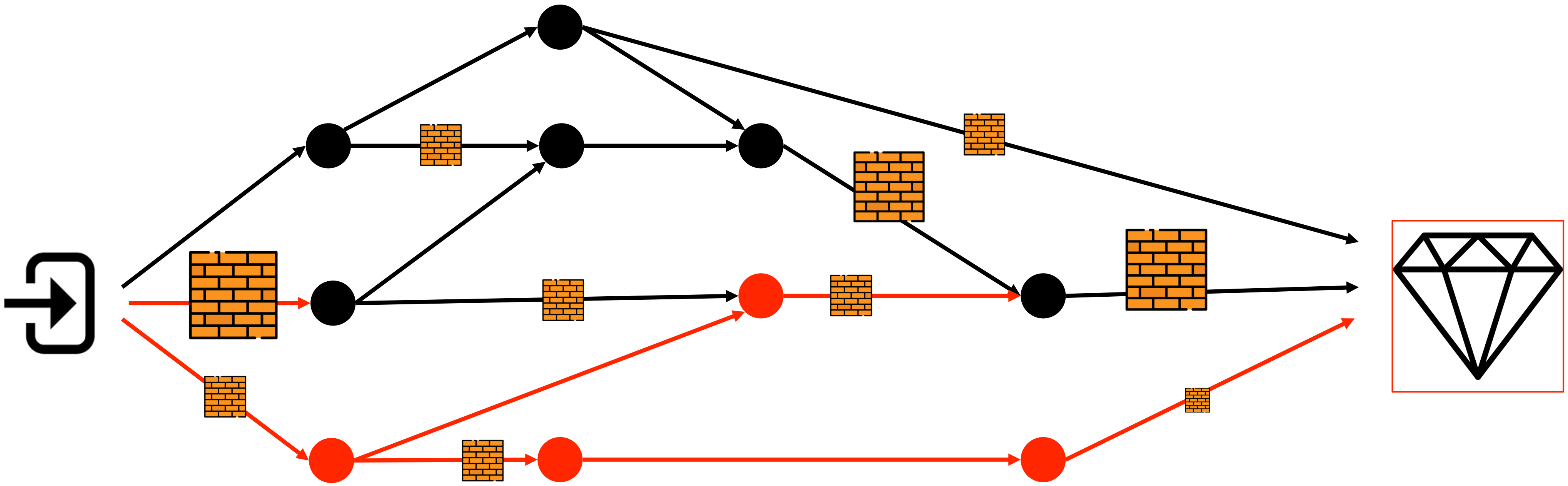
Pivoting: Intruder is not stupid!

https://lingchunkai.github.io/pdf/AICS-2025.pdf



- Nodes: Machines, servers, routers
- Edges: Potential vulnerabilities
- Walls: Defenses controls to be beefed up, subject to budget/performance constraint

Given intruder's action **changes with time as they explore the network,** how should defenses be placed?

*Interesting connection with the Gittins index, ongoing work

Ongoing research

Dealing with stochastic actions sets (looking for students!)
- Not all actions available, can we still solve this **efficiently**?

Security games with discovery (looking for students)
- Attacker doesn't actually know the full network, need to account for that or else defender is at too big a disadvantage

Structured reward functions that are defined formally by commonly used semantics (e.g., PCTL, LTL)
- Can we still get fast algorithms?

Structured eqm are very interesting, but assumptions not necessarily true
- E.g., Gittins policy can be quite brittle, make several assumptions, but necessary for tractibility
- How can we handle slight deviations from these assumptions?
- Do we swing all the way to deep learning? Or is there a better balance between the 2?

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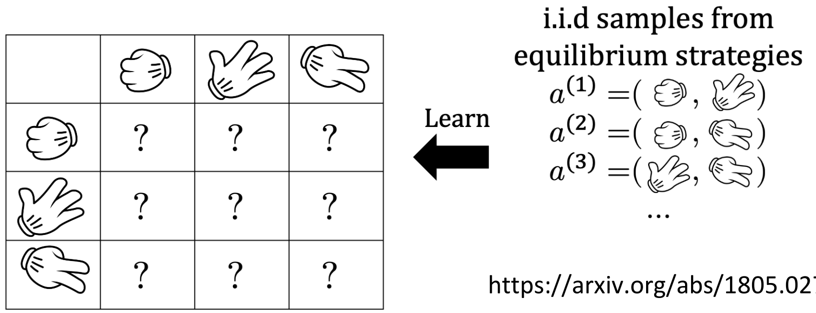
*Yes, I know the audience here…

- Exact solutions: very rarely (outside of recreational games)
  - Does the 6^{th} significant digit matter if the model itself is inaccurate?

Inverse Game Theory/Computational Rationalization

- Explain **why** players are behaving the way they do



https://arxiv.org/abs/1805.02777

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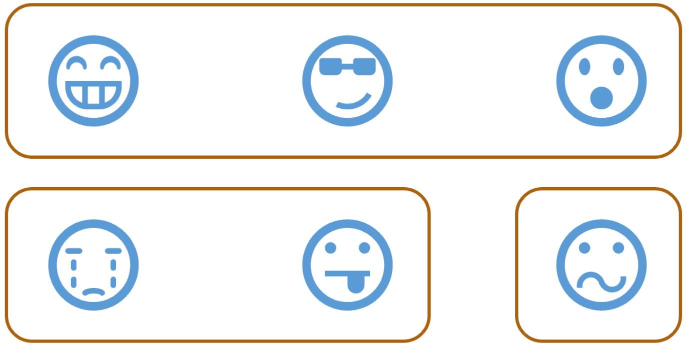
IGT via differentiable optimization



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Coalition Structure Learning

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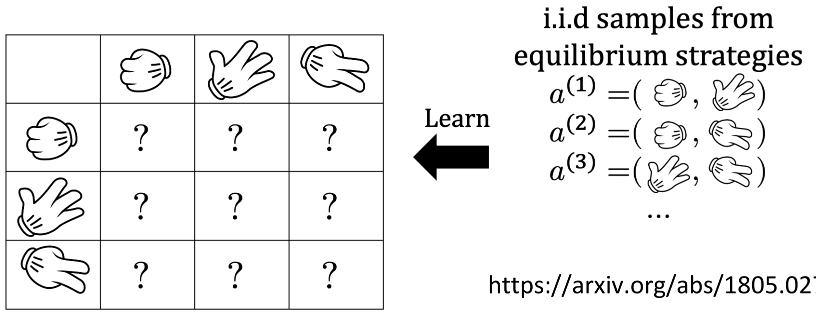

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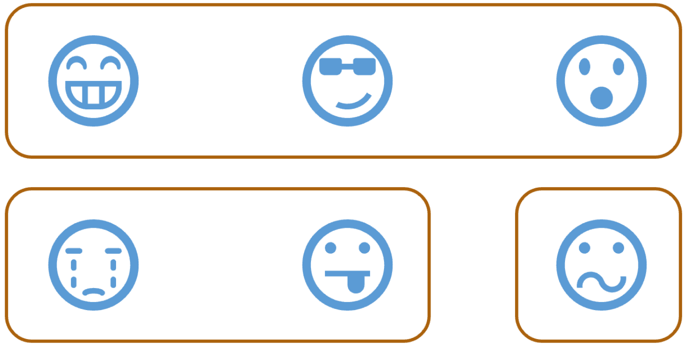

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Coalition Structure Learning

Learning strategies that **are** interpretable/operationalizable

- Restriction to strategies that are compact e.g., product distributions, sparse
- Regularization to “human-like” strategies

Explaining equilibrium selection

*ongoing work

Direction 3: Challenging Assumptions

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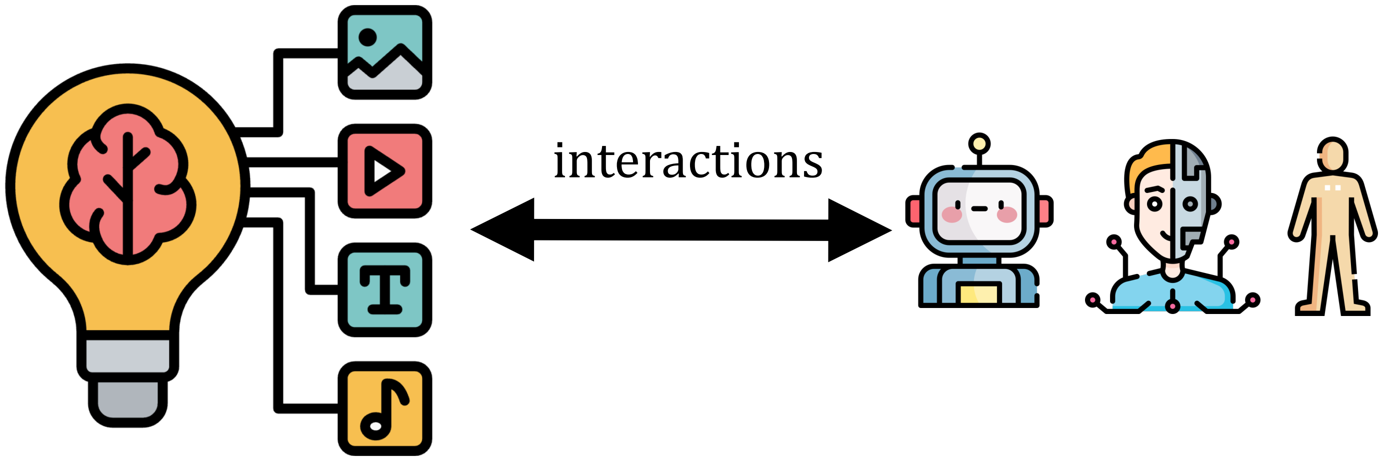
Tackle new *problems* by allowing interactions in human modalities

- Example: language models used in bargaining, negotiations
- How to incorporate strategy into such high-modality, fluid action spaces?
    - Strategically eliciting information from other language agents *ongoing work



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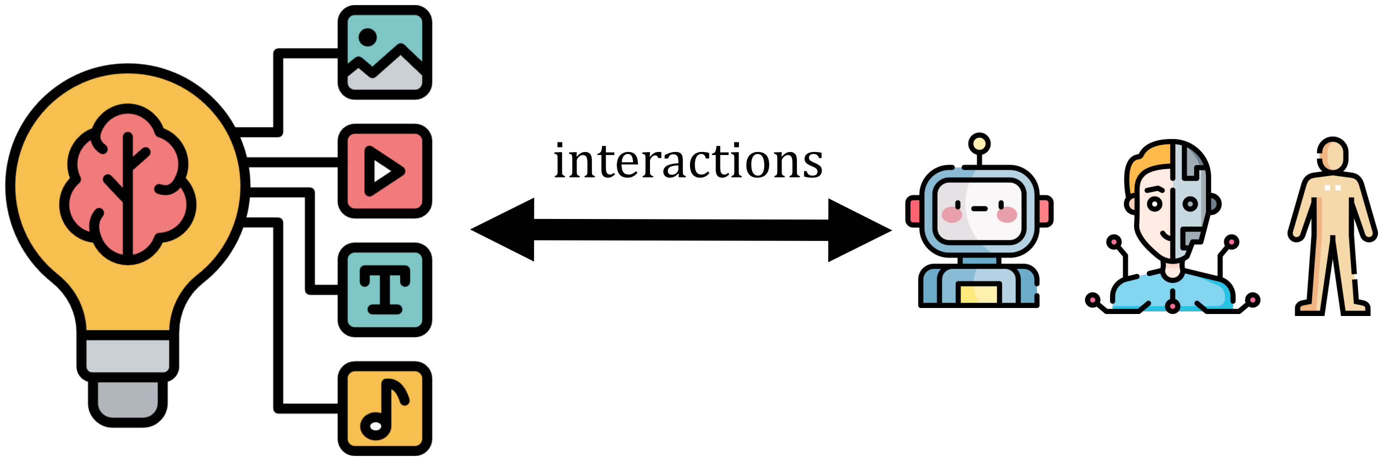


What about games without common prior?

Are equilibrium even the right concept?

Ongoing Projects

Learning **robust** strategies in a interactive setting

- Game of twenty questions

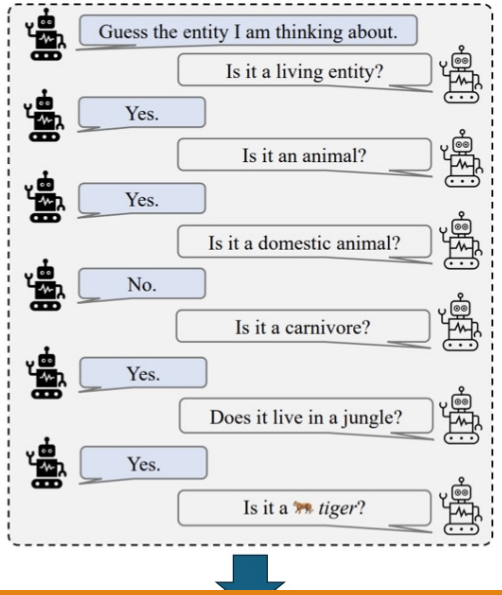
Explaining **strategies** to humans in a **meaningful** way

- Useful for persuasion, or just learning in general
- Much more tricky, need to care about **counterfactuals**

In general, for many of these problems…

- Behavior off the equilibrium path matters **a lot**
- Big difference between single agent and multiagent

Game of 20 Questions as an Extensive Form Game (EFG



Any Questions?

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Contact me if you'd like to collaborate!