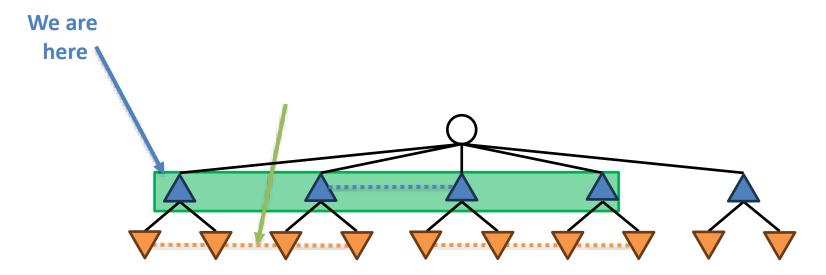
Safe subgame resolving

Safe subgame solving is based on the common-knowledge subgame **Definition**:

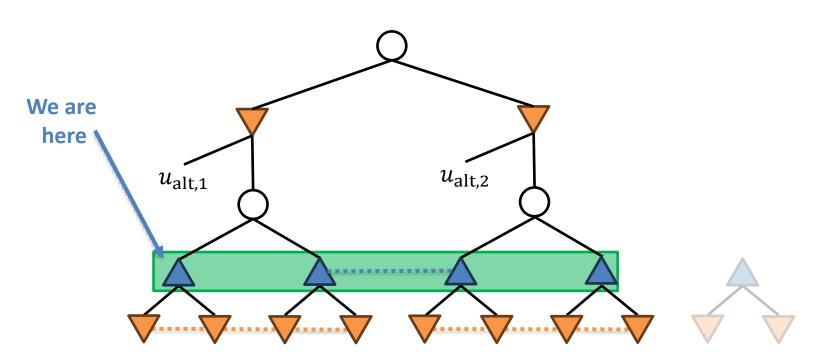
- Two nodes in the same layer of the game tree are connected if there is an infoset connecting some descendant of the first node to some descendant of the second node
- The **common-knowledge subgame** at a node h consists of all nodes recursively connected to h, and all their descendants.



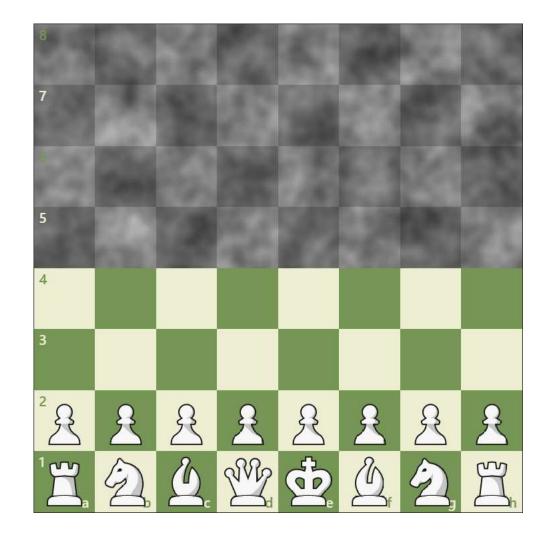
Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021

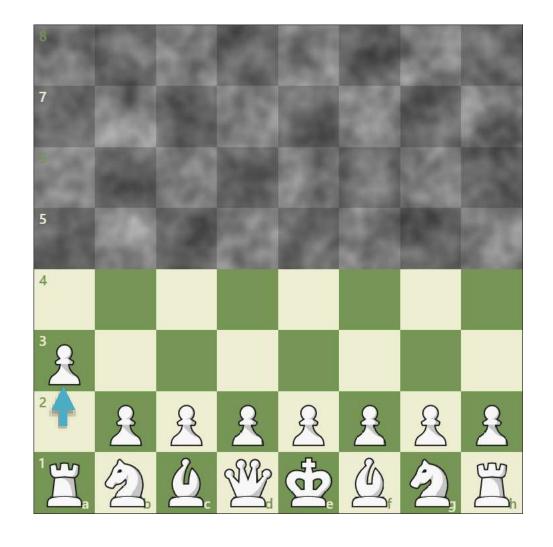
Safe subgame resolving

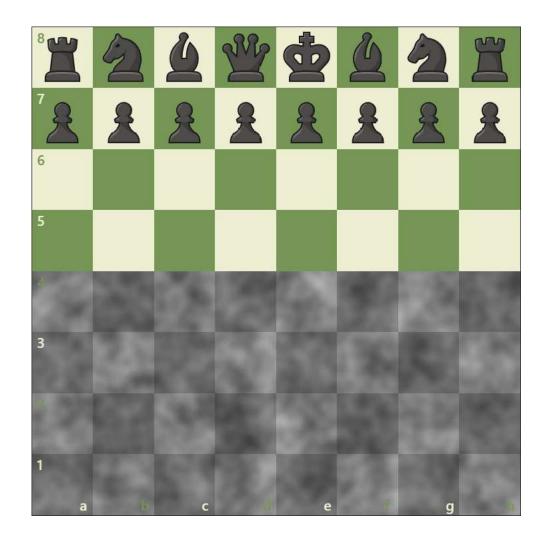
Resolve gadget game:

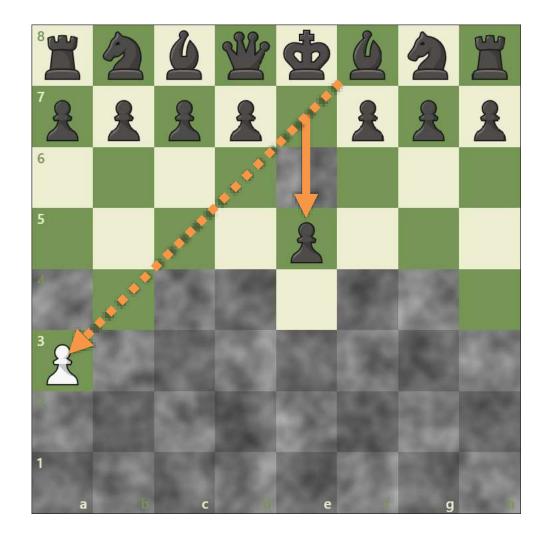


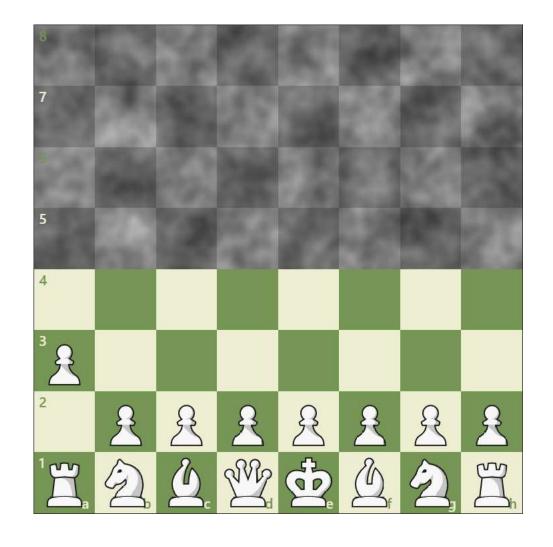
Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021

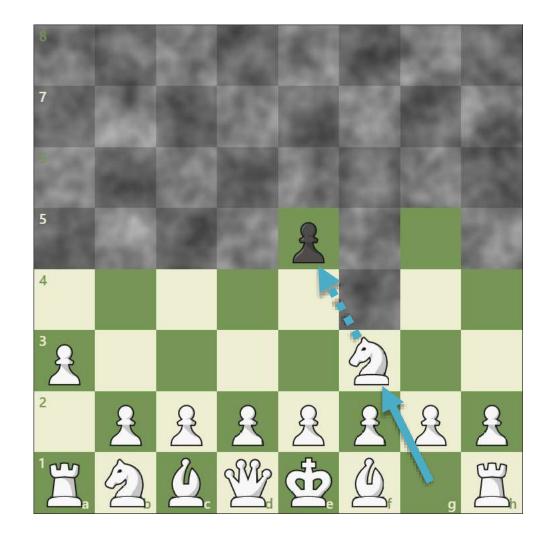


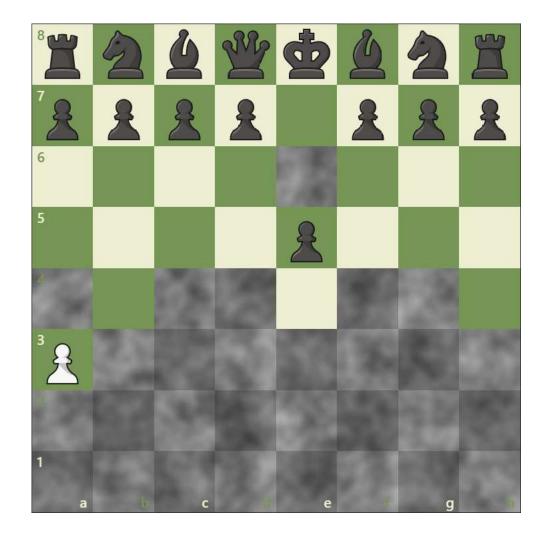


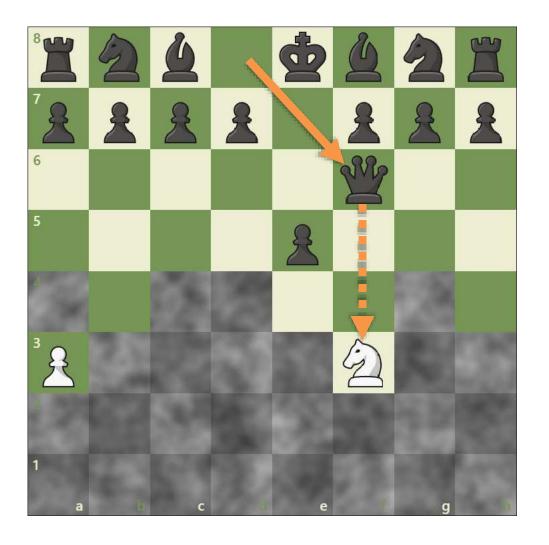


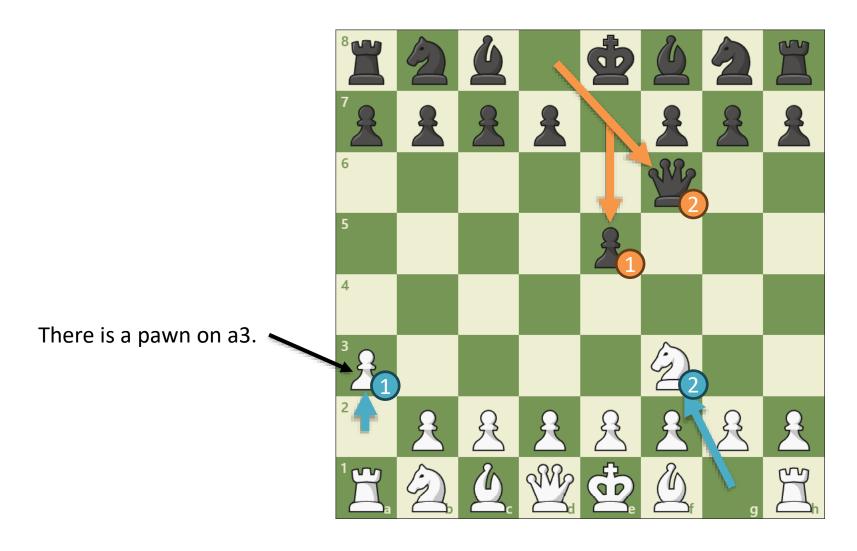


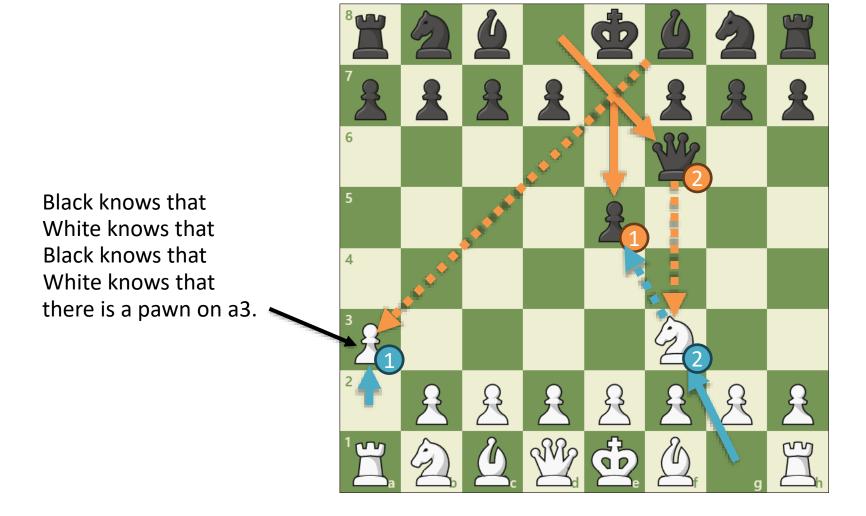






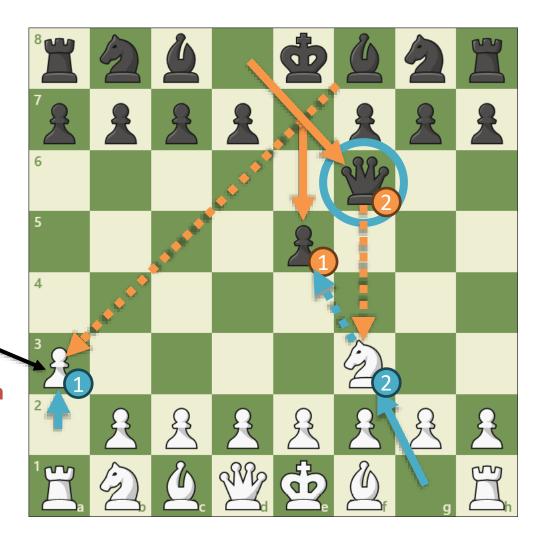






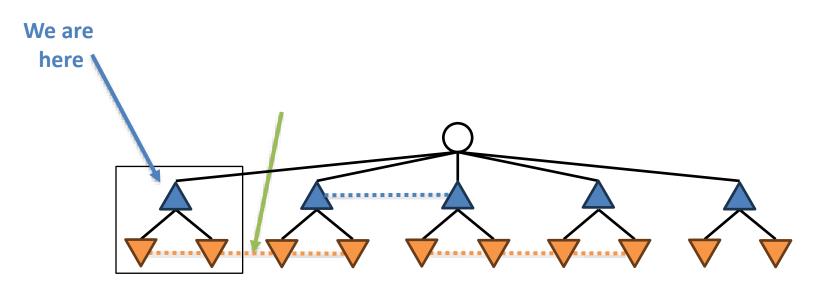
Does White know that Black knows that White knows that Black knows that White knows that there is a pawn on a3?

No! White didn't see the queen



Subgame solving in imperfectinformation games

We cannot solve the subgame in isolation, because the solution may depend on the remainder of the game

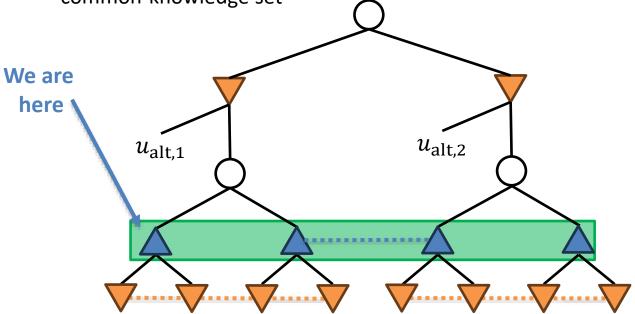


Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021

So, what is the problem?

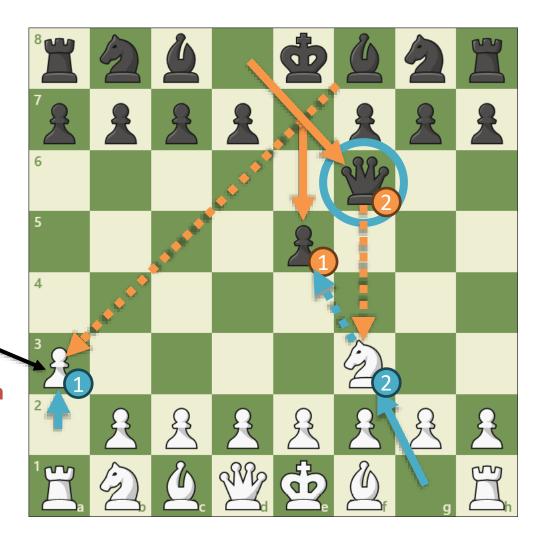
- Common-knowledge sets can be very large!
 - Heads-up Texas hold'em: $|C| < 2 \times 10^6$
 - Manageable in real time
 - Practical tricks [Johanson et al *IJCAI*-11] mean that, effectively, $C \approx 10^3$
 - Dark chess: Common for C to be too large to store in memory, much less work with in real time

 Not even obvious how to determine whether two nodes are in the same common-knowledge set

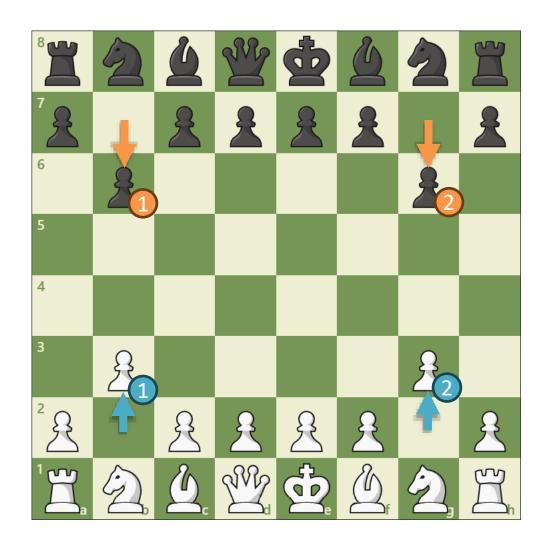


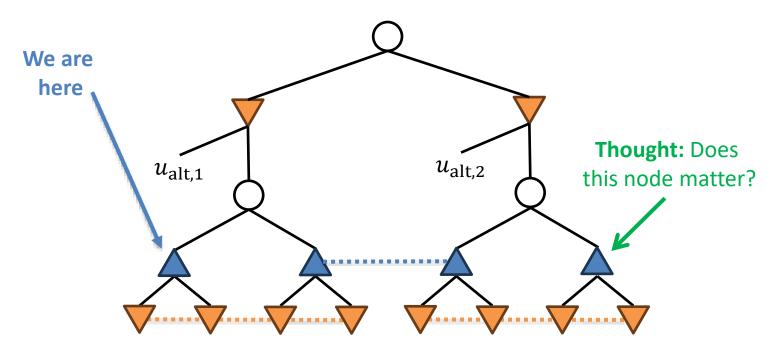
Does White know that Black knows that White knows that Black knows that White knows that there is a pawn on a3?

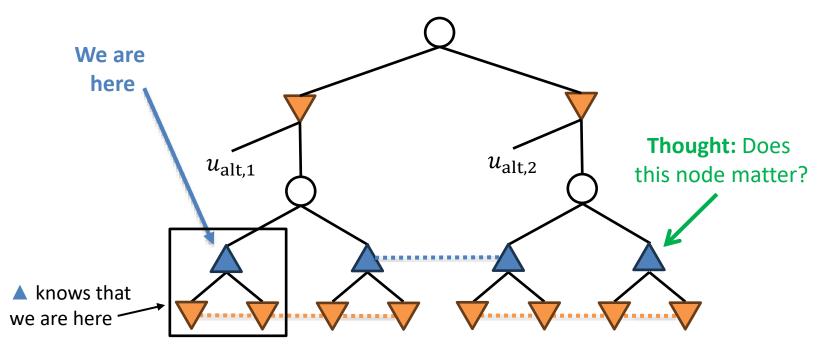
No! White didn't see the queen



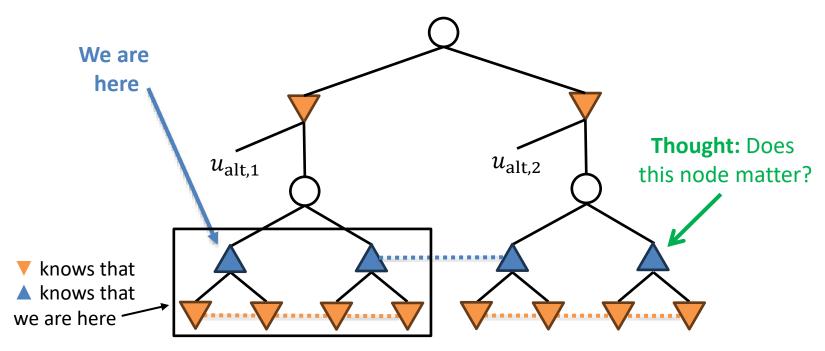
This game state is in the same common-knowledge set as the previous one!



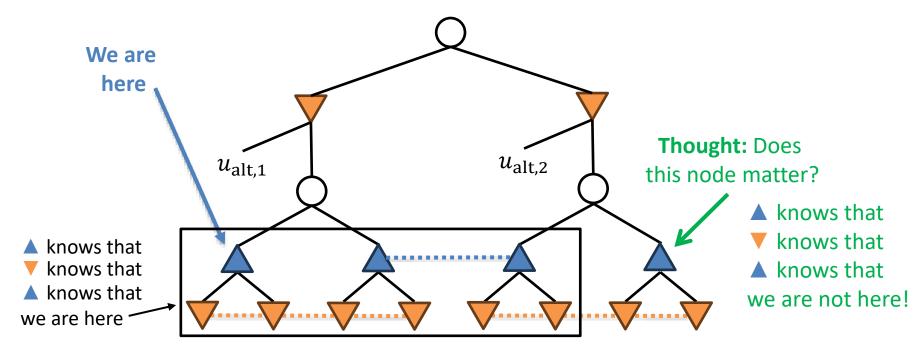




Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021



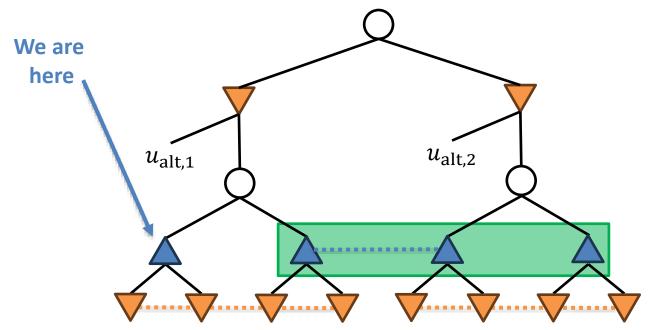
Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021



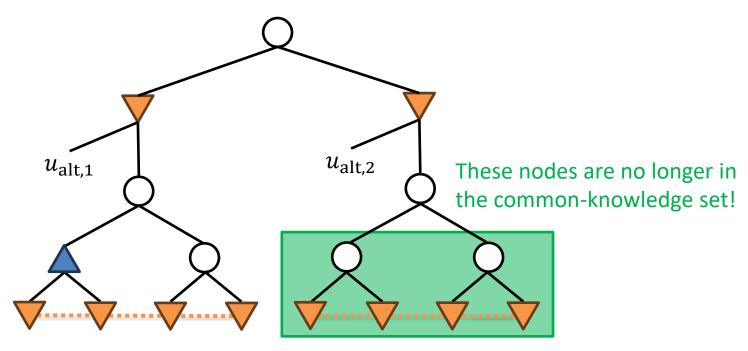
Zhang and Sandholm, "Subgame solving without common knowledge", NeurIPS 2021

Idea: Assume that we will not deviate from the blueprint at nodes no longer reachable

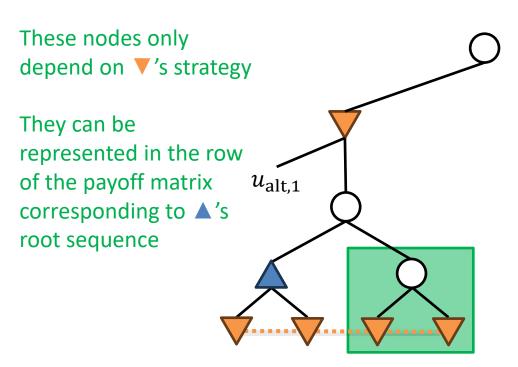
They become chance nodes with fixed probabilities



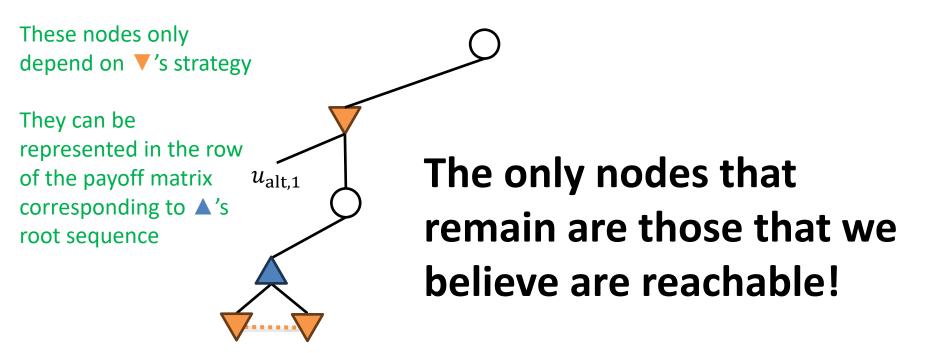
Now let us see what happens if we run subgame solving as usual



Now let us see what happens if we run subgame solving as usual



Now let us see what happens if we run subgame solving as usual



Is it safe in theory?

No. Easy counterexample:

- N copies of matching pennies. Chance chooses the copy. Max knows which copy we are playing, but Min does not
- Blueprint: Max plays Heads w.p. $\frac{1}{2} + \frac{2}{N}$ in all copies
- KLSS: With all other infosets fixed, Max switching to "always play tails" in one infoset results in a more balanced strategy
- Thus, after KLSS, Max always plays tails!
- Intuition: KLSS will overcorrect for systematic errors in the blueprint

Is it safe in practice?

Yes!

• Even when the blueprint has bad systematic errors (the blueprints in these experiments were ε -noisy Nash equilibria for $\varepsilon=0.25$)

	expl		
game	blueprint	after 1-KLSS	ratio
2x2 Abrupt Dark Hex	.0683	.0625	1.093
4-card Goofspiel, random order	.171	.077	2.2
4-card Goofspiel, increasing order	.17	.0	∞
Kuhn poker	.0124	.0015	8.3
Kuhn poker (ε -bet)	.0035	.0	∞
3-rank limit Leduc poker	.0207	.0191	1.087
3-rank limit Leduc poker (ε -fold)	.0065	.0057	1.087
3-rank limit Leduc poker (ε -bet)	.0097	.0096	1.011
Liar's Dice, 5-sided die	.181	.125	1.45
100-Matching pennies	.0013	.0098	0.13

Dark chess

- Large game
 - Game tree is almost identical to that of regular chess
- Moderate-sized information sets
 - Size $\approx 10^5$ to 10^6 is common, but $> 10^7$ is very rare
- Unmanageable common-knowledge sets
 - Common-knowledge sets likely have size $> 10^{12}$
 - Enumeration is impractical in real time
- Our techniques allow the creation of a strong agent!

Dark chess

Advantages over naïve techniques:

- Our bot can bluff and exploit the opponent's lack of knowledge.
- Our bot can mix accurately, which is important in many situations.
 - A bot that does not mix at all in Dark Chess is easily exploitable!

Weaknesses of the bot:

- Due to how the bot handles information and chooses what nodes to expand, it assumes the opponent knows more than they actually do.
- "Iterative deepening" subgame search does not prune very well due to the randomness necessary to play dark chess well, so subgame solves are relatively low-depth and will miss tactics.

Dark chess

Performance:

- Comfortably better than me
 - I am \approx 1700 on chess.com
- Lost to the world #1 human (≈2400) 9-1
- Strong opening and middlegame play; weak endgame play (plays too conservatively)

KLSS is unsafe. Why? conditional best response value to x at J conditional best response value to x at J to x_0 at JMargin $J(x) = \min_{y_J} u_J(x, y_J) - \min_{y_J'} u_J(x_0, y_J')$

 y_I, y_I' : strategy for ∇ following J

 u_S : value conditional on reaching set S

x: \triangle 's resolved strategy in subgame

 x_0 : \triangle 's blueprint strategy

J: an infoset for ▼

Recall: Every strategy with positive margins is safe

Liu, Fu, Yang, "Opponent-Limited Online Search for Imperfect Information Games", *ICML* 2023

KLSS is unsafe. Why? conditional best response value to
$$x$$
 at J conditional best response value to x at J conditional best response value to x_0 at J

Margin $J(x) = \min_{y_J} \left\{ u_J(x, y_J) - \min_{y_J'} u_J(x_0, y_J') \right\}$

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KLSS is unsafe. Why?

$$\operatorname{Margin}_{J}(x) = \min_{y_{J}} \left\{ u_{J}(x, y_{J}) - u_{J}(x_{0}, y_{J}) \right\}$$

$$y_J, y_J'$$
: strategy for ∇ following J

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J: an infoset for ▼

$$+ u_{J}(x_{0}, y_{J}) - \min_{y'_{J}} u_{J}(x_{0}, y'_{J})$$

Recall: Every strategy with positive margins is safe

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KLSS is unsafe. Why?

Unsafe KLSS assumes only one of these terms can be nonzero at a time

$$\operatorname{Margin}_{J}(x) = \min_{y_{J}} \left\{ \sum_{I} \beta(I) \left(u_{I \cap J}(x_{I}, y_{J}) - u_{I \cap J}(x_{0;I}, y_{J}) \right) \right\}$$

$$y_I, y_I'$$
: strategy for ∇ following J

 u_S : value conditional on reaching set S

x: \triangle 's resolved strategy in subgame

 x_0 : \triangle 's blueprint strategy

/: an infoset for ▼

I: an infoset for ▲

 $x_I, x_{0,I}$: \triangle 's resolved/blueprint following I

 $\beta(I)$: P1 reach probability of I according to blueprint

Recall: Every strategy with positive margins is safe

$$+ u_{J}(x_{0}, y_{J}) - \min_{y'_{J}} u_{J}(x_{0}, y'_{J})$$

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Theorem: This is a safe way to do KLSS!

Safe KLSS

KLSS is unsafe. Why?

$$\operatorname{Margin}_{I,J}(x) = \min_{y_J} \left\{$$

$$\operatorname{Margin}_{I,J}(x) = \min_{y_I} \left\{ \beta(I) \left(u_{I \cap J}(x_I, y_J) - u_{I \cap J}(x_{0;I}, y_J) \right) \right\}$$

"allows one infoset *I* to steal the whole gift" Solution: Use gift-splitting, like in reach maxmargin!

$$y_J, y_J'$$
: strategy for ∇ following J
 u_S : value conditional on reaching set S

$$x$$
: \triangle 's resolved strategy in subgame

$$x_0$$
: \triangle 's blueprint strategy

$$x_I, x_{0,I}$$
: \triangle 's resolved/blueprint following I

$$\beta(I)$$
: P1 reach probability of I according to blueprint

Recall: Every strategy with positive margins is safe

$$+ u_{J}(\boldsymbol{x_{0}}, \boldsymbol{y_{J}}) - \min_{\boldsymbol{y_{J}'}} u_{J}(\boldsymbol{x_{0}}, \boldsymbol{y_{J}'})$$

difference between y_I 's value at Jagainst blueprint, and its best response value against blueprint

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Game	Blueprint	Unsafe	Maxmargin	Resolving	1-KLSS	Safe-1-KLSS
Leduc(2,3,1)	0.150	0.195	0.109	0.089	0.190	0.120
Leduc(2,3,1)	0.150	0.142	0.115	0.113	0.132	0.127
Leduc(2,13,1)	0.150	0.044	0.084	0.065	0.453	0.127
Leduc(2,13,2)	0.150	0.077	0.127	0.089	1.091	0.128
Leduc(2,13,3)	0.150	0.089	0.113	0.090	1.108	0.117
FHP	10.640	5.077	6.153	6.142	97.313	8.334

Takeaways from these experiments:

- In practice, unsafe subgame solving often does pretty well!
- Safe KLSS is...
 - better than unsafe KLSS (unsurprisingly)
 - almost as good as common-knowledge subgame solving!