Robust Strategies and Counter-Strategies: From Superhuman to Optimal Play

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January 14, 2016

Grad Seminar

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Computer Poker Research Group

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Games as a testbed for Artificial Intelligence

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- Surpassed humans in 1994
- Solved (perfect play) in 2007

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Current challenges (not yet superhuman):
go, Atari 2600 games, General Game Playing,
Starcraft, RoboCup, poker, curling (?!) and so on…

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Babbage and Lovelace:
Wanted “Games of Purely Intellectual Skill” to demonstrate their Analytical Engine.
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John von Neumann:
Founded **Game Theory** to study rational decision making.
Needed computational power to drive it, became pioneer in Computing Science.

Core idea in this line of research:

We aspire to create agents that can
achieve their goals in complex real-world domains.

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Can play against humans, to compare
Artificial Intelligence to Human Intelligence.

John von Neumann pioneered Game Theory.
When asked about real life and **chess**, he said…

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When asked about real life and **chess**, he said…

Real life is not like that.

Real life consists of bluffing,
of little tactics of deception,
of asking yourself what is the other man
going to think I mean to do.

And that is what games are
about in my theory.

Chess is a..

2-player,

deterministic,

perfect information game,

with win / lose / tie outcomes.

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2-10 Players (at one table)
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Cards randomly dealt
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Opponent's cards are hidden.

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Poker:

2-10 Players (at one table)
Thousands (tournaments)

Stochastic:
Cards randomly dealt to players and the table.

Imperfect Information:
Opponent’s cards are hidden.

Maximize winnings by exploiting opponent errors.

My Research and This Grad Seminar

Topic: Computing strong strategies
in Imperfect Information Games

2008:
PhD Start

2015:
PhD End

My Research and This Grad Seminar

Two key milestones
in 2-Player limit hold'em poker:

2008:
PhD Start

2015:
PhD End

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First computer
victory over
human poker
pros.

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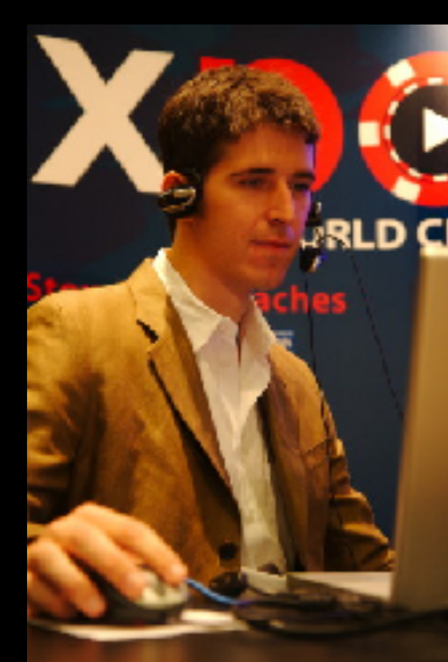

My Research and This Grad Seminar

Two key milestones
in 2-Player limit hold'em poker:

2008:
PhD Start

First computer victory over human poker pros.

2015:
PhD End

Game solved. Computer is now optimal.

>= Everyone, forever.

My Research and This Grad Seminar

Two key milestones
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First computer victory over human poker pros.

Solving Attempt #1

Solving Attempt #2

Solving Attempt #3…

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First computer victory over human poker pros.

2015:
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Game solved. Computer is now optimal.

Note: I'll be **very** high-level in this talk.
This is a summary of 7 papers in my thesis,
and 7 more not in my thesis.
Ask questions!

Superhuman Play:

The **Abstraction-Solving-Translation** Procedure.

This is how we beat the pros in 2008.

First used in poker by Shi and Littman in 2002.

Still the dominant approach in large games.

Terminology:

Strategy: A policy for playing a game.
At every decision, a probability
distribution over actions.

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Best Response: A strategy that maximizes utility against a specific target strategy.

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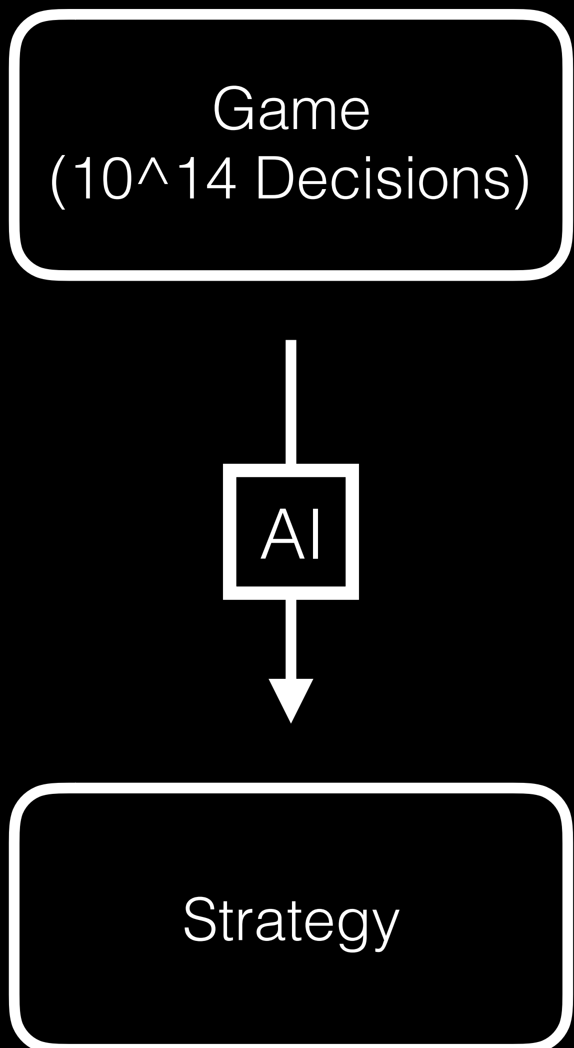
Best Response: A strategy that maximizes utility against a specific target strategy.

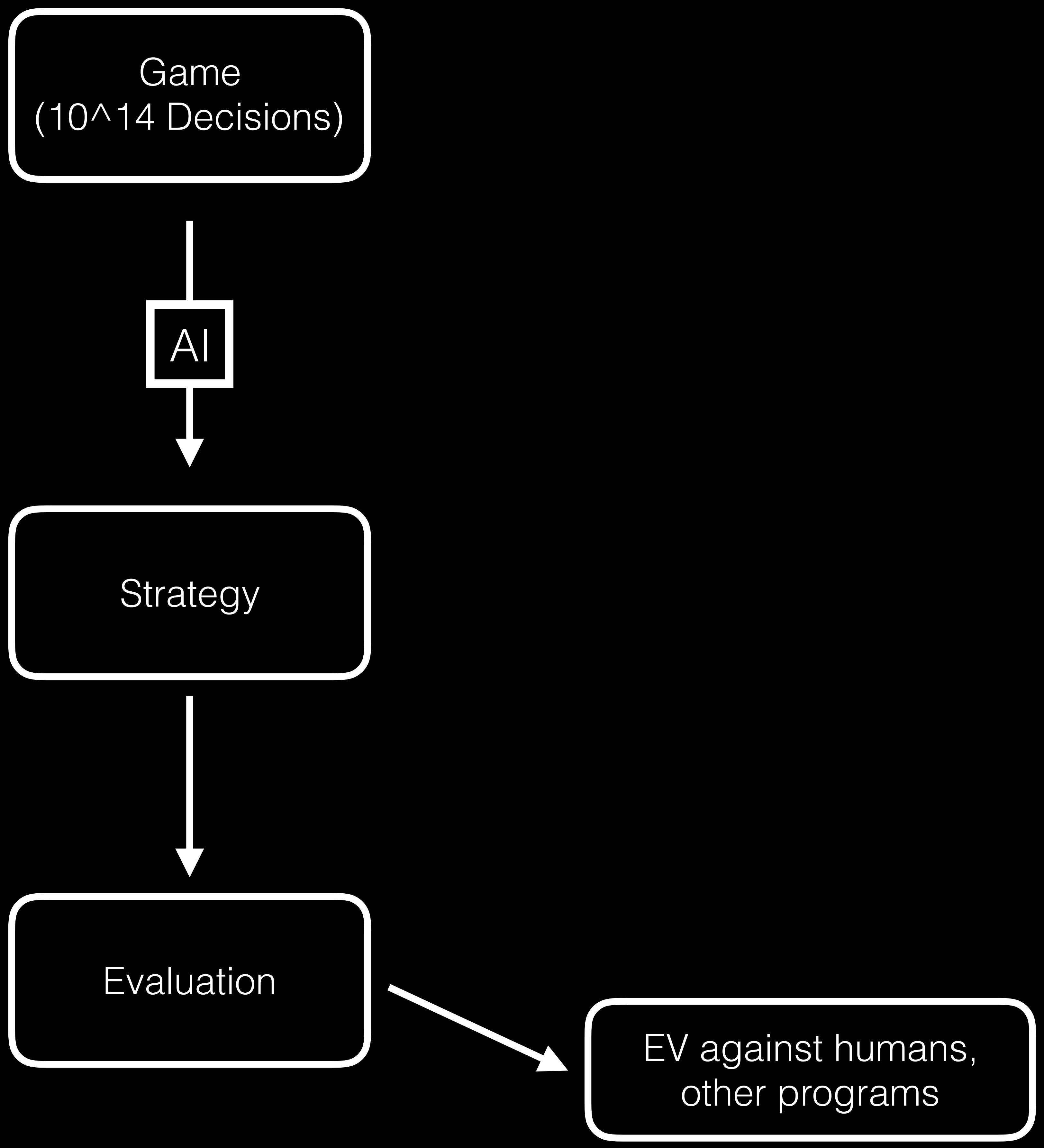
Nash Equilibrium: A strategy for every player that are all mutually best responses to the others.

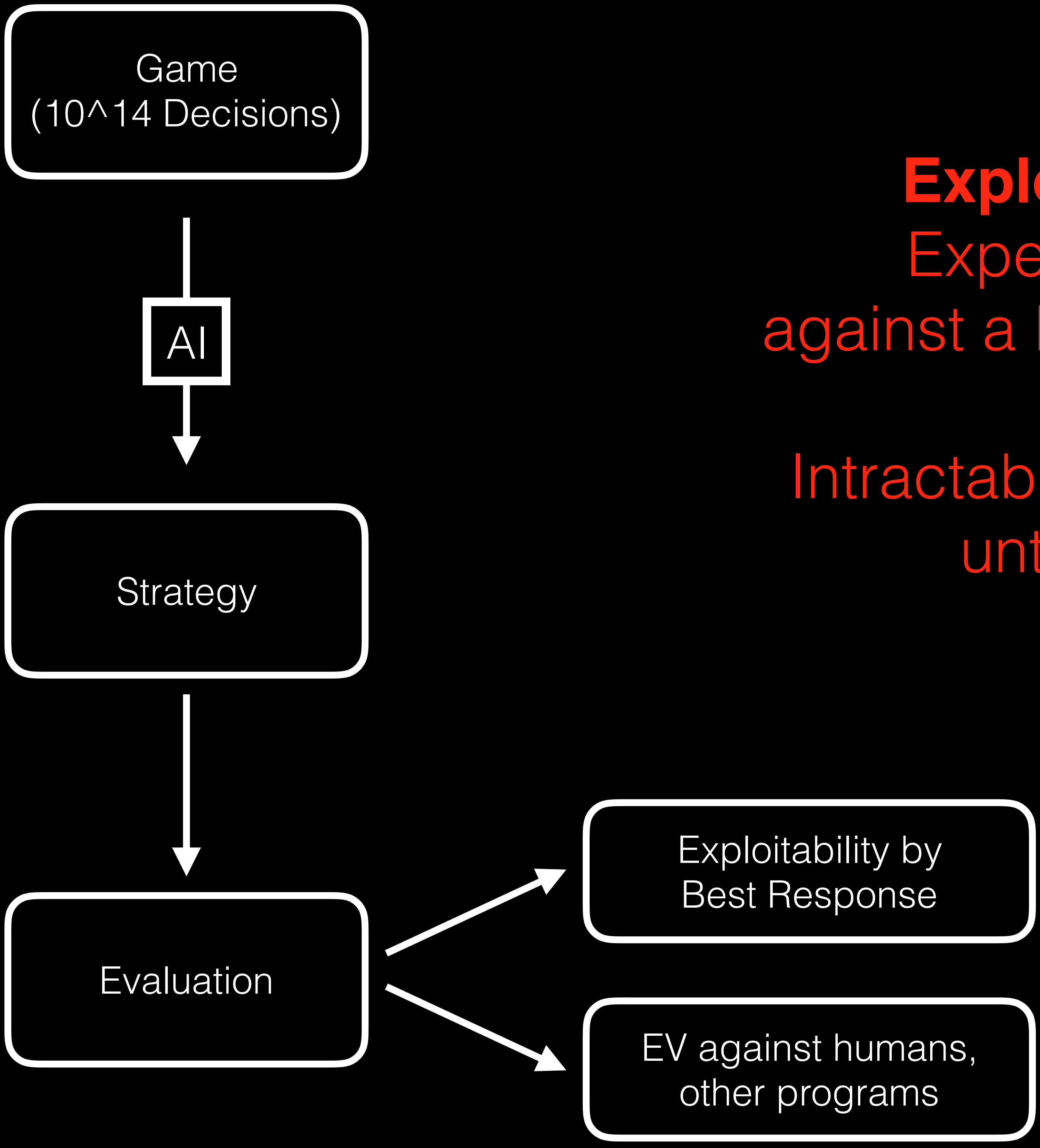
In a 2-player zero-sum game, it's guaranteed to do no worse than tie.



Solve the game by computing a Nash Equilibrium.

(Opponent Modelling comes later)


Game
(10^14 Decisions)
AI
Strategy
Evaluation
EV against humans,
other programs



Exploitability:
Expected loss
against a best response.

Intractable to compute
until 2011.

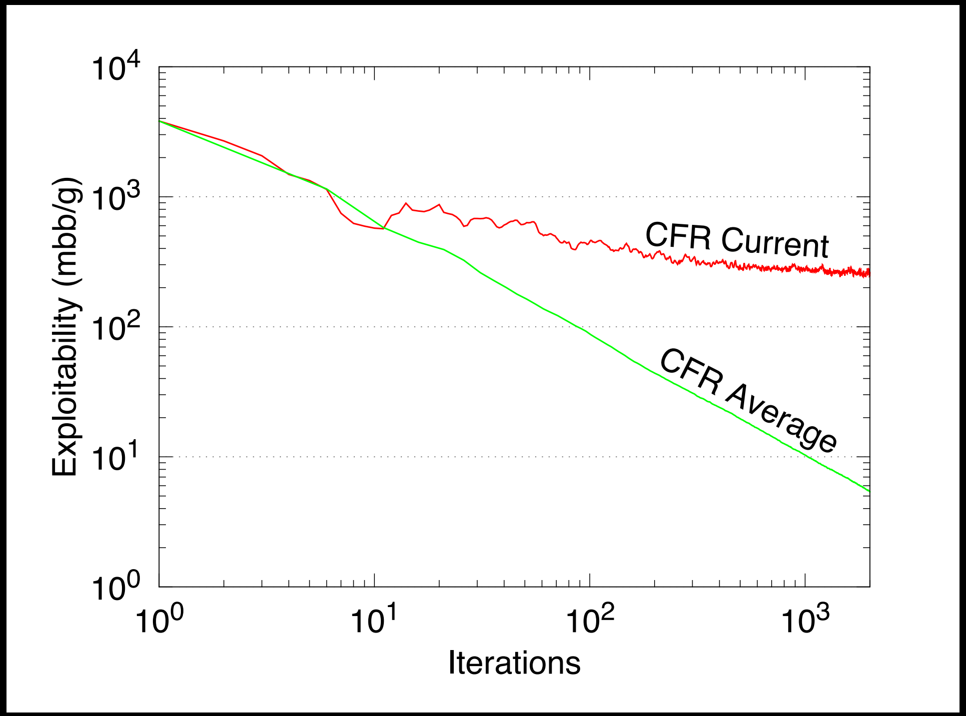
The AI Step: Counterfactual Regret Minimization (CFR)

1. Start with Uniform Random strategy.

2. Repeatedly plays against itself.  vs 

2a. Update: At each decision, use the historically best actions more often. (minimizing regret)

3. Average strategy converges towards a Nash equilibrium.



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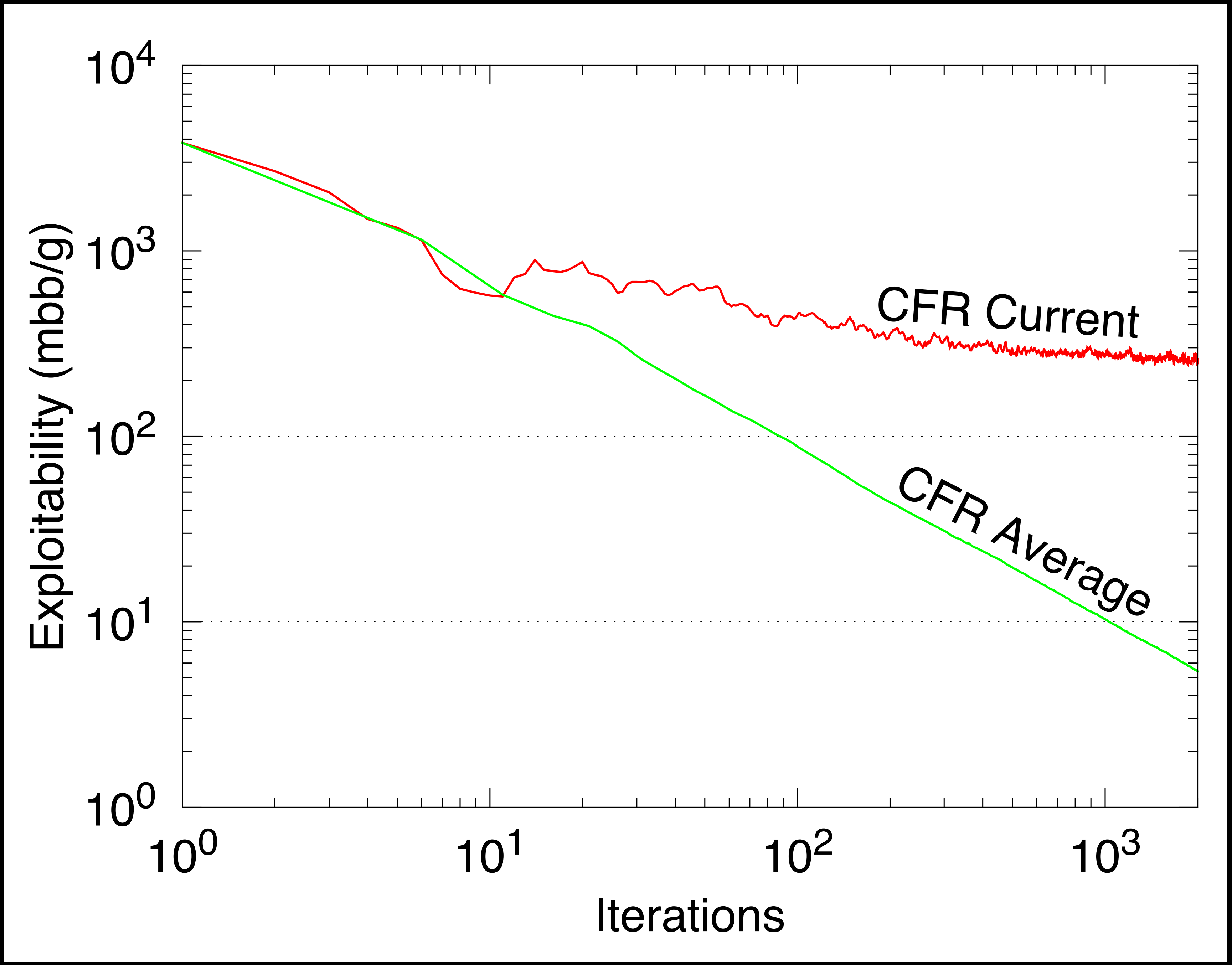
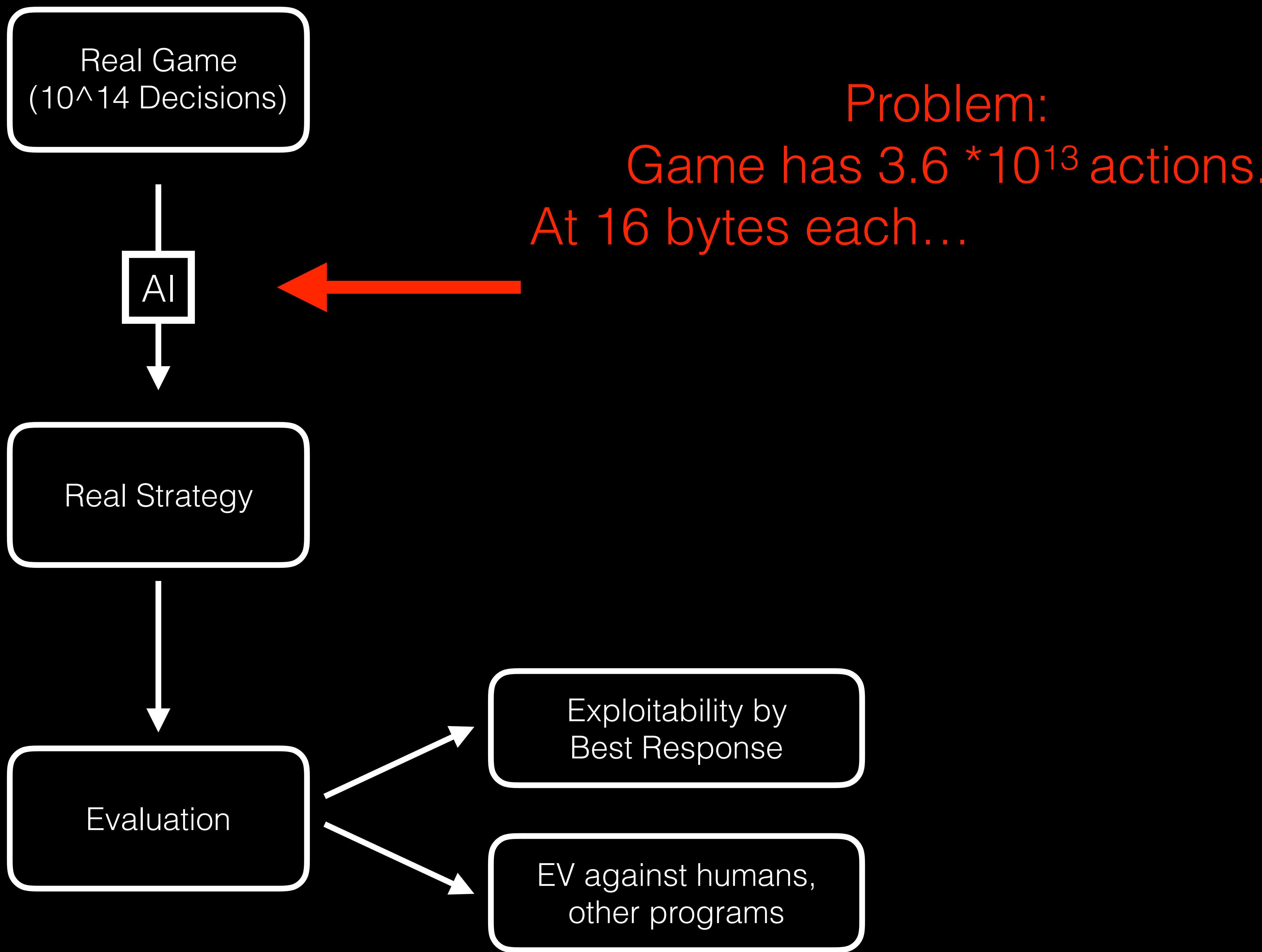
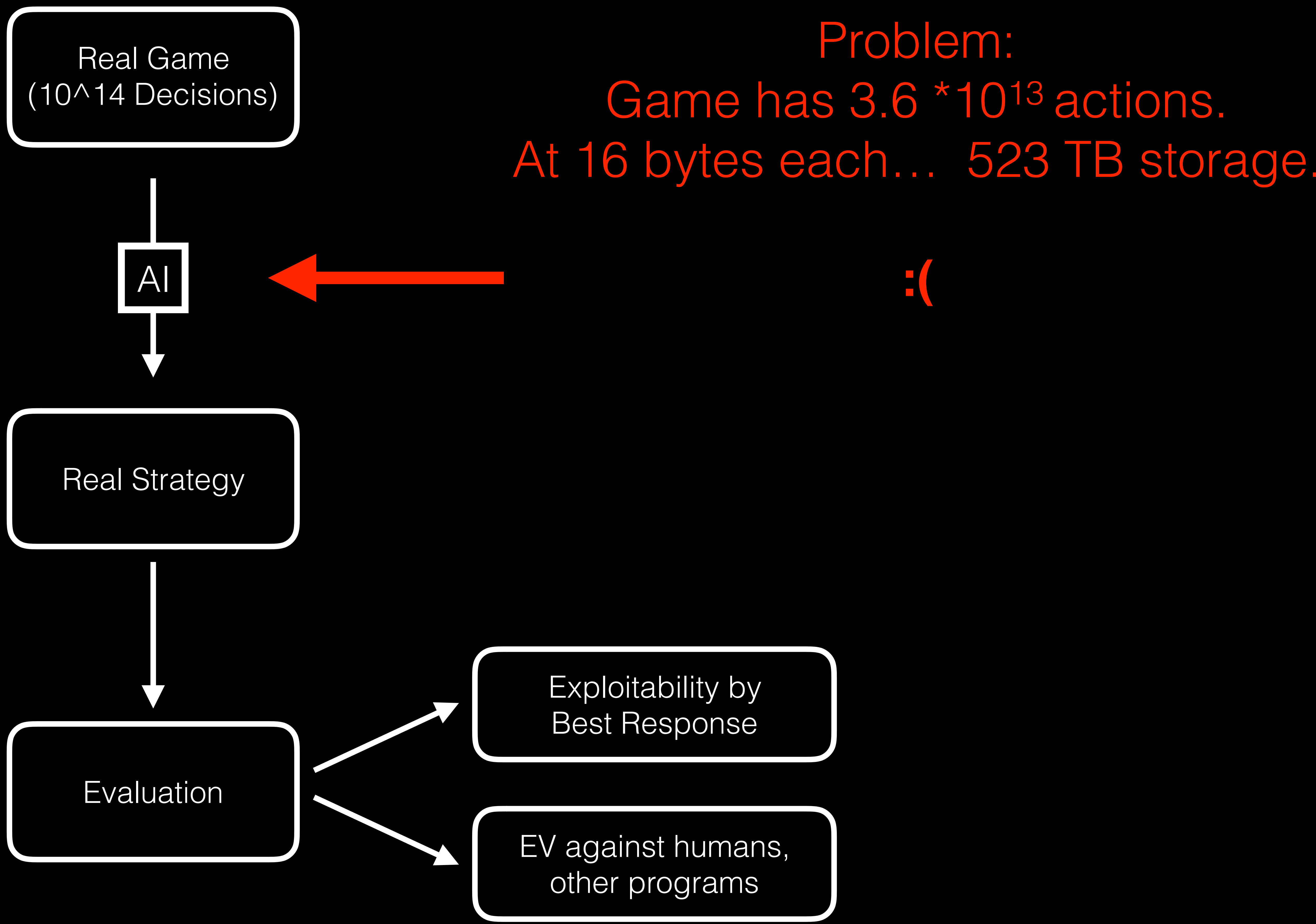


Memory Cost: **2 doubles** per **Action-at-Decision-Point**
(16 bytes)


Real Game
(10^14 Decisions)
AI
Real Strategy
Evaluation
Exploitability by
Best Response
EV against humans,
other programs
Problem:
Game has $3.6 * 10^{13}$ actions.
At 16 bytes each…



Real Game
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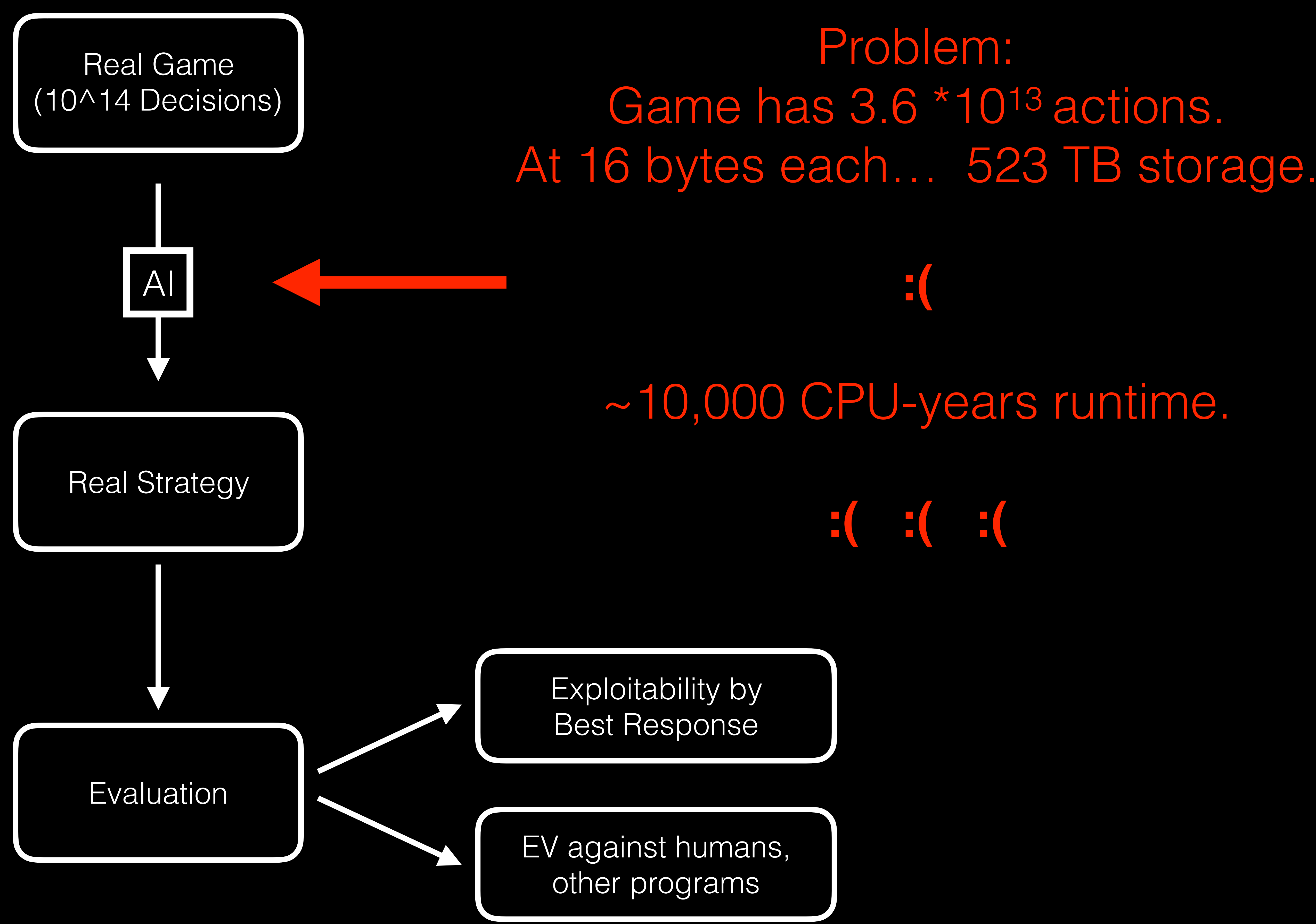
Problem:
Game has 3.6 *10^13 actions.
At 16 bytes each… 523 TB storage.
:(


Real Game
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Problem:
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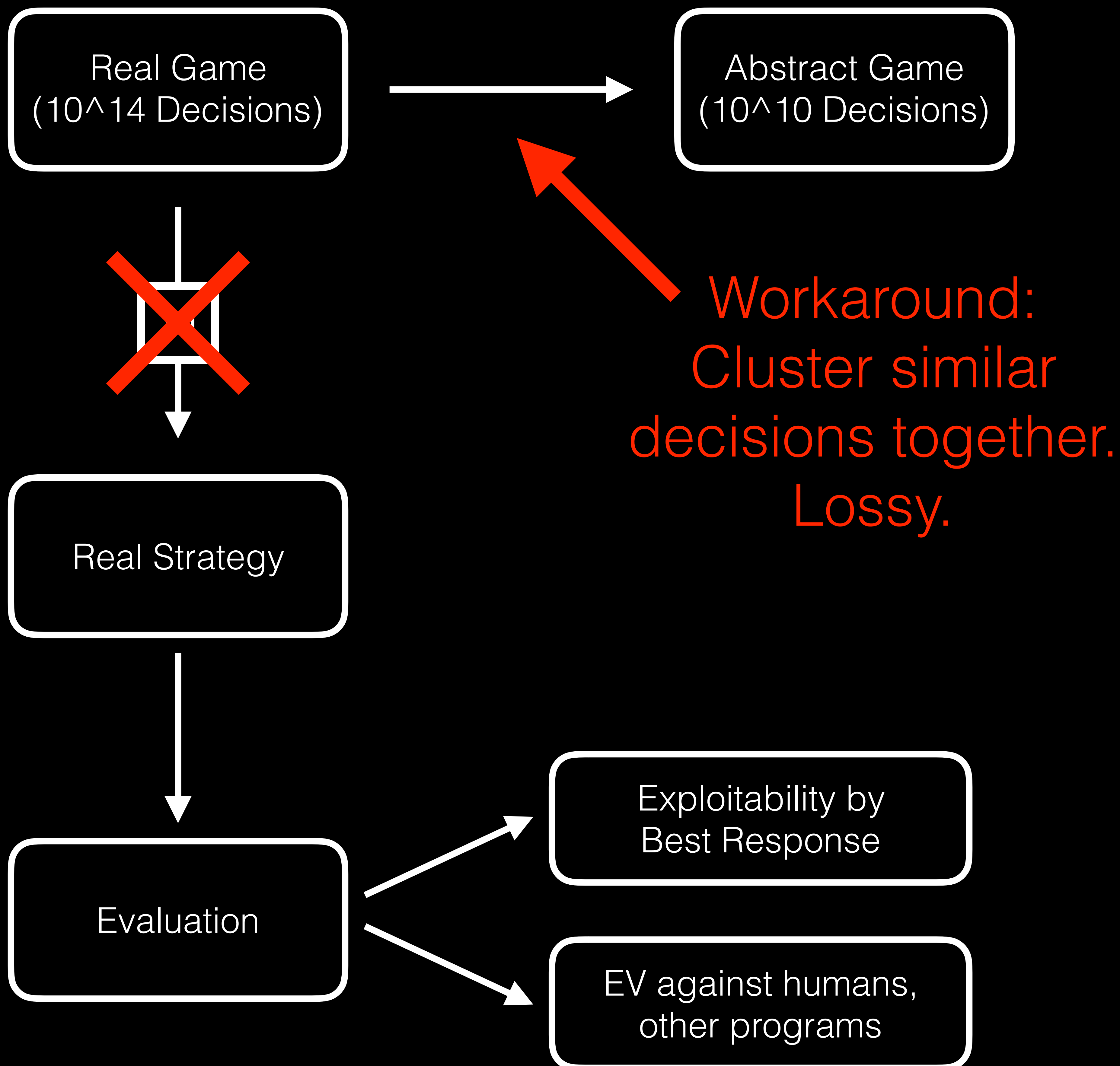
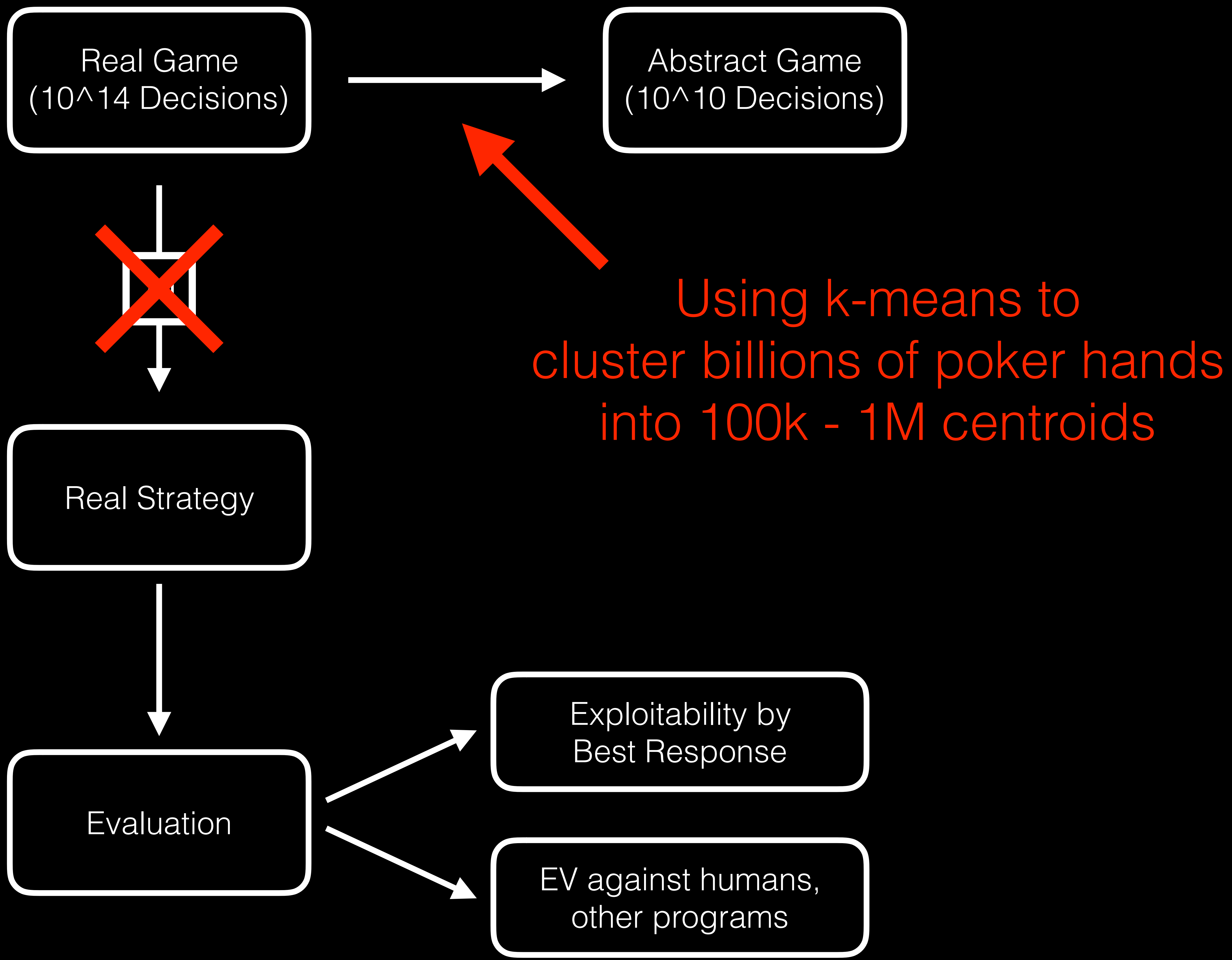
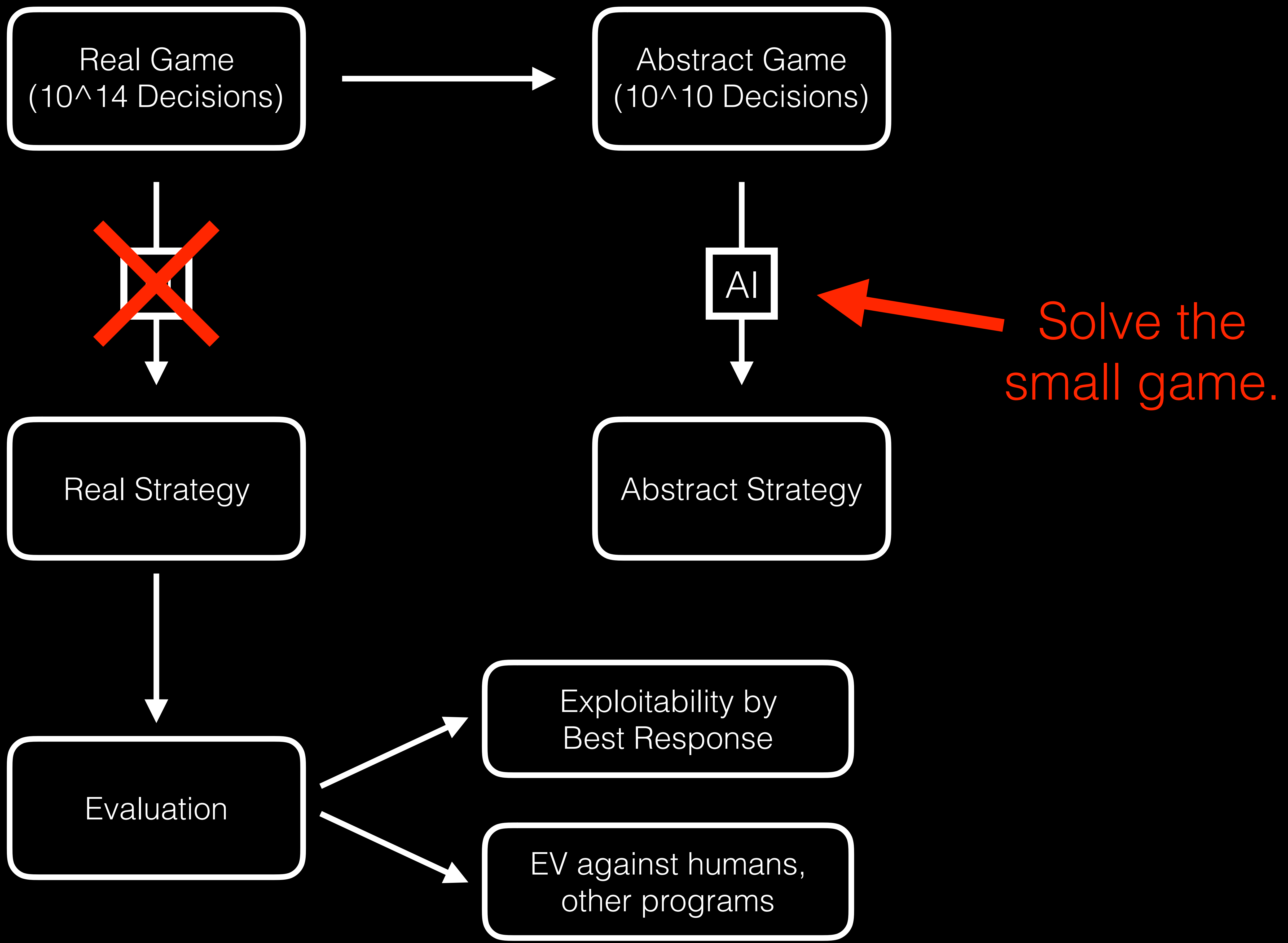
~10,000 CPU-years runtime.
:(:(:(

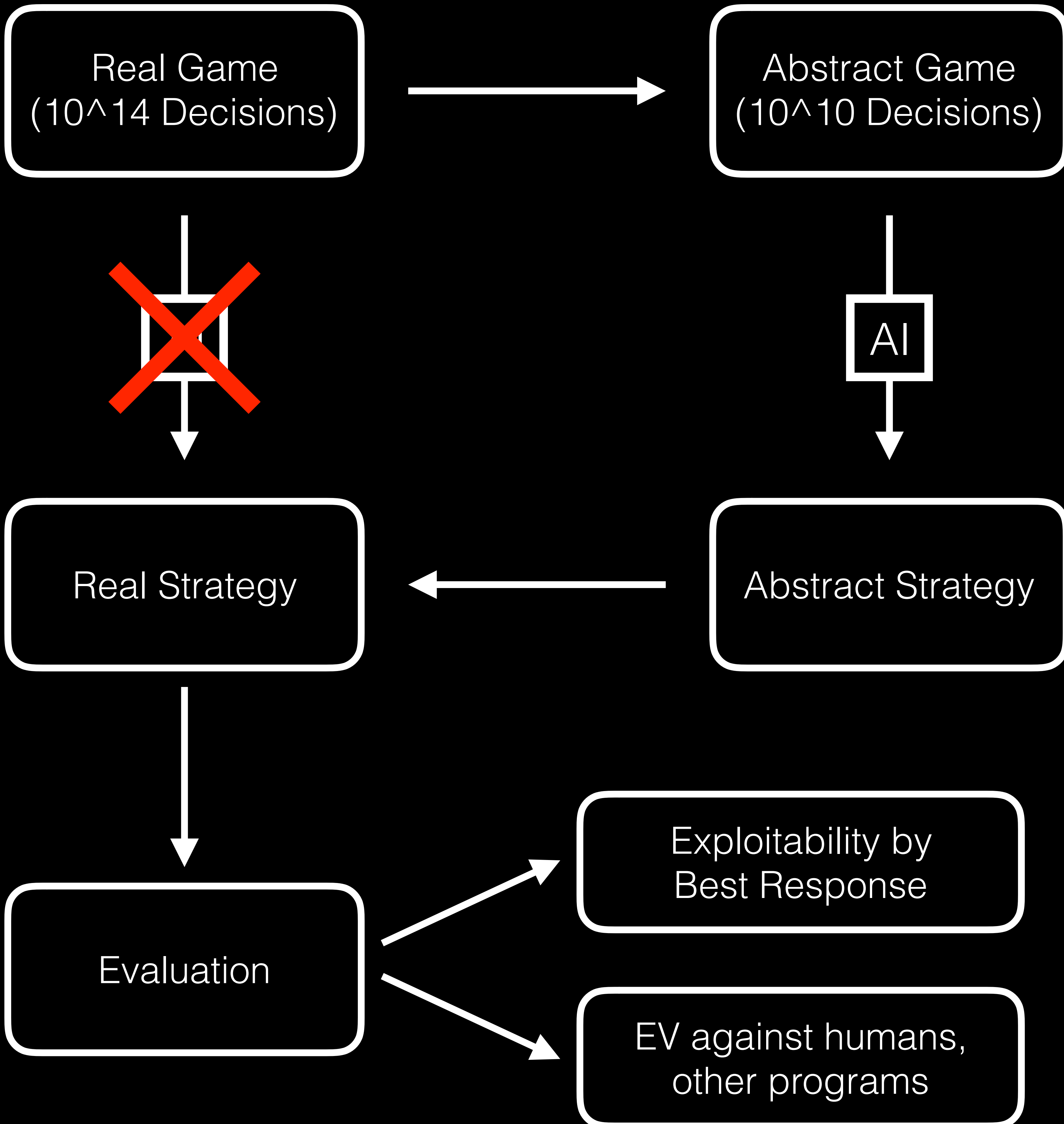

Real Game
(10^14 Decisions)
Abstract Game
(10^10 Decisions)
Workaround:
Cluster similar
decisions together.
Lossy.
Real Strategy
Evaluation
Exploitability by
Best Response
EV against humans,
other programs



Real Game
(10^14 Decisions)
Abstract Game
(10^10 Decisions)
Using k-means to
cluster billions of poker hands
into 100k - 1M centroids
Real Strategy
Evaluation
Exploitability by
Best Response
EV against humans,
other programs

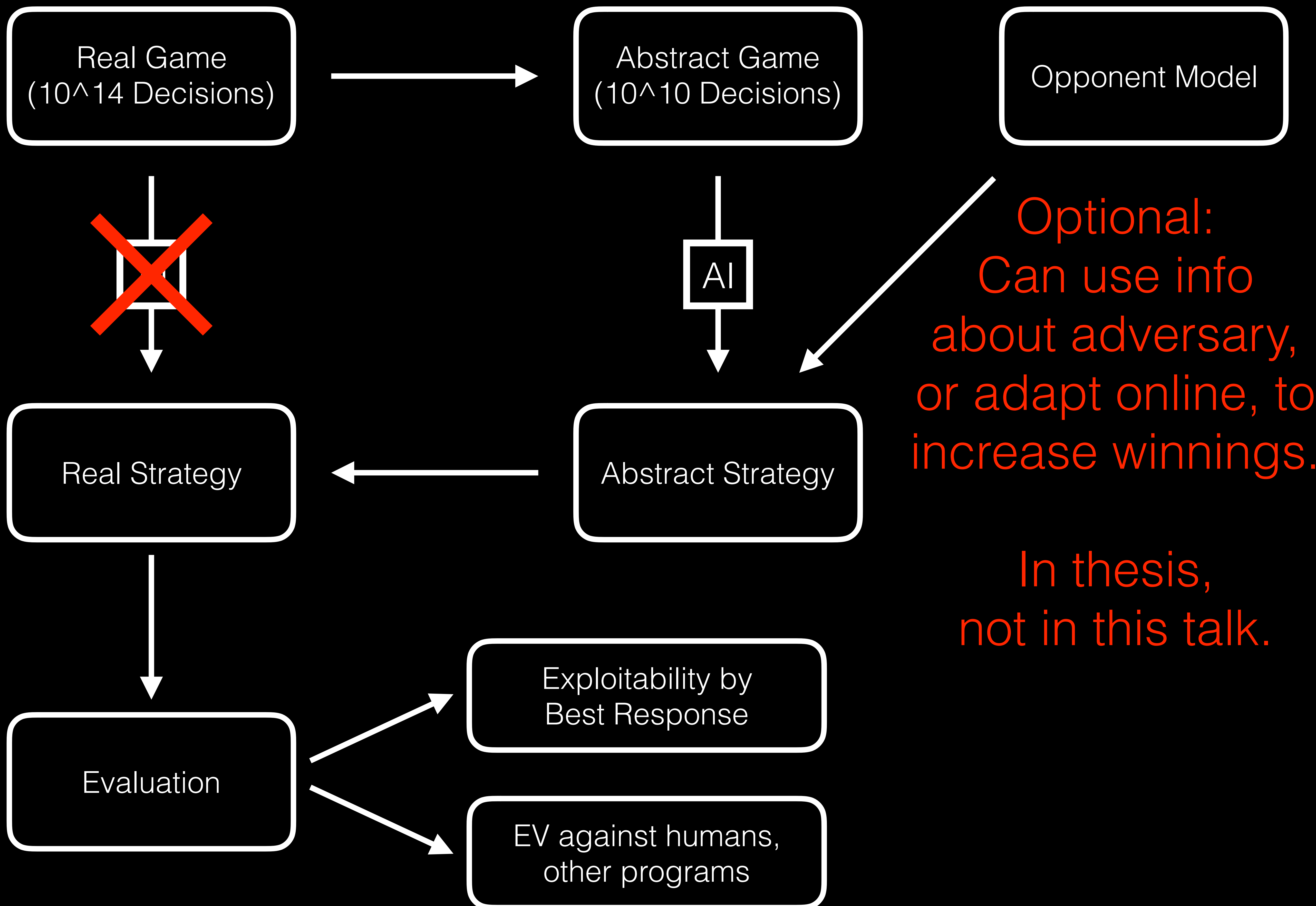


Real Game
(10^14 Decisions)
Abstract Game
(10^10 Decisions)
AI
Solve the
small game.
Real Strategy
Abstract Strategy
Evaluation
Exploitability by
Best Response
EV against humans,
other programs



Use small strategy
to act in the
real game.

NOTE:
Not optimal!
Lossy abstraction!


Real Game
(10^14 Decisions)
Abstract Game
(10^10 Decisions)
Opponent Model
AI
Optional:
Can use info
about adversary,
or adapt online, to
increase winnings.
In thesis,
not in this talk.
Real Strategy
Abstract Strategy
Evaluation
Exploitability by
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EV against humans,
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Intuition:

Using abstraction limits the strategy’s strength.

Merging decisions together loses information.

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Bigger (finer-grained)
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Better (feature-preserving)
abstractions

$\Rightarrow$

Better Strategies:
wins more,
less exploitable

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Bigger (finer-grained)
and
Better (feature-preserving)
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→

Better Strategies:
wins more,
less exploitable

Better Computers,
Better Algorithms

→

Can solve
bigger abstractions

Abstraction-Solving-Translation was enough to beat top human pros.

In retrospect, it was easy:
~8 GB RAM, a few CPU-days.
Fairly small abstractions, too!

2007: Narrow loss. 4 GB strategy.
2008: Narrow win. 8 GB strategy.

In 2011, we discovered that these strategies were VERY exploitable.

The Man-vs-Machine strategies were beatable, but small.

At the time, we thought: to be optimal, maybe we just have to solve a big enough abstraction!

If we can reduce exploitability to “1 milli-big-blind”, then it’s *essentially* solved.

Close enough - justification later in this talk.

Solving Attempt #1 (2008-2011):

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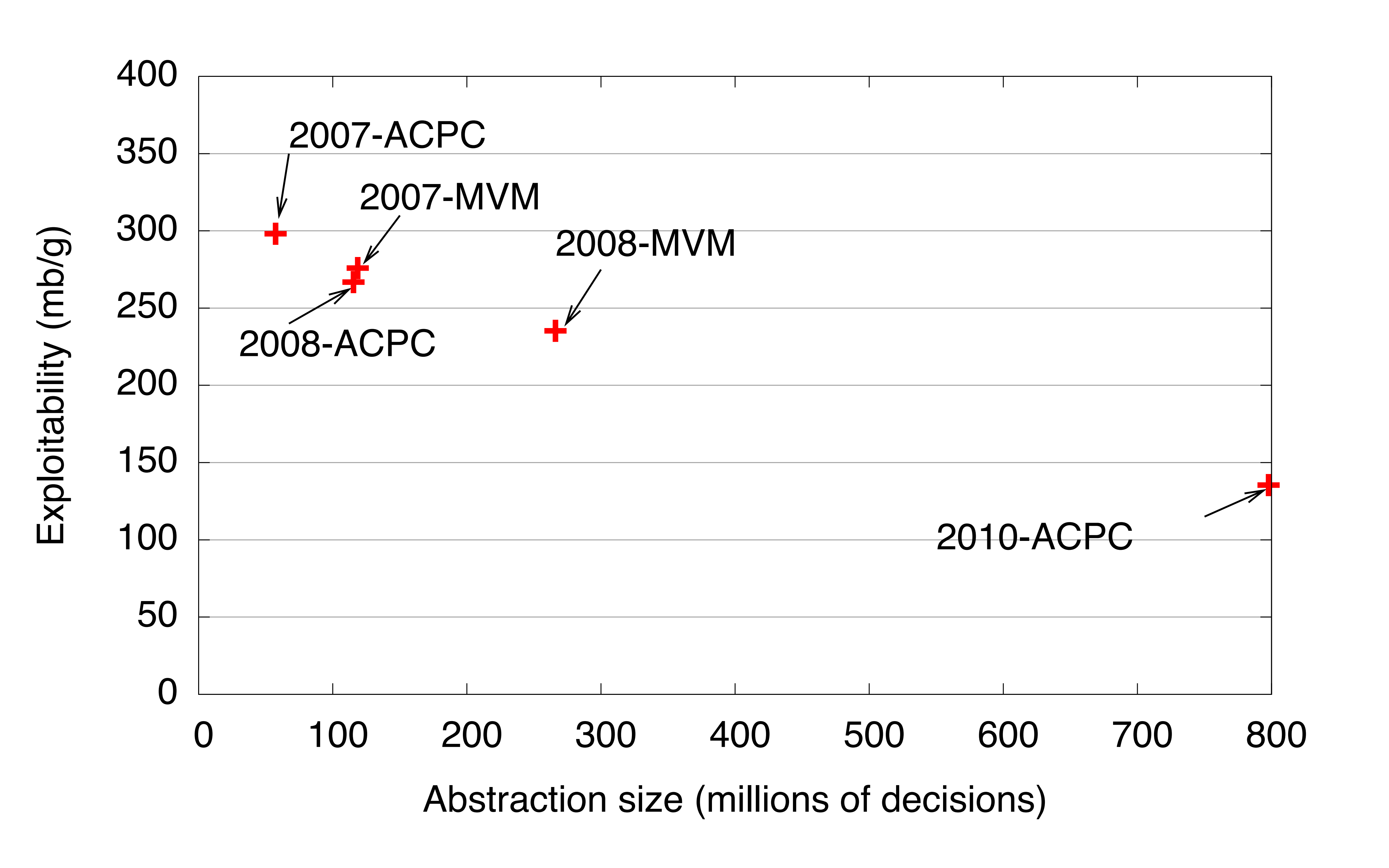
In 2011, we wrote a fast algorithm for
finding perfect real-game counter-strategies.
(IJCAI 2011)

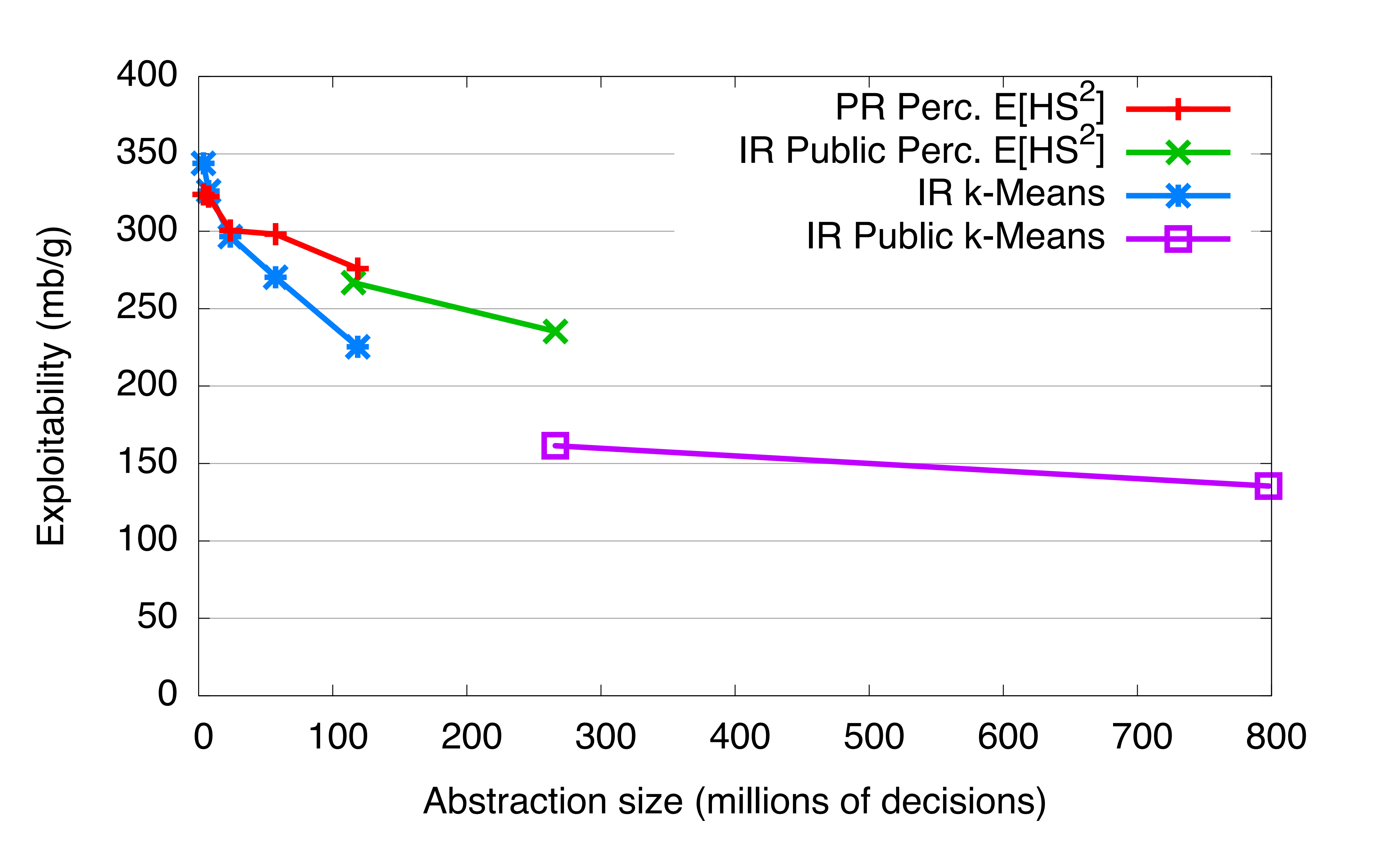
For the first time, we could measure
exploitability!

We turned a 10 CPU-year computation into
a 76 CPU-day computation. 1 day on the cluster.

Looking back at 5 years of progress!

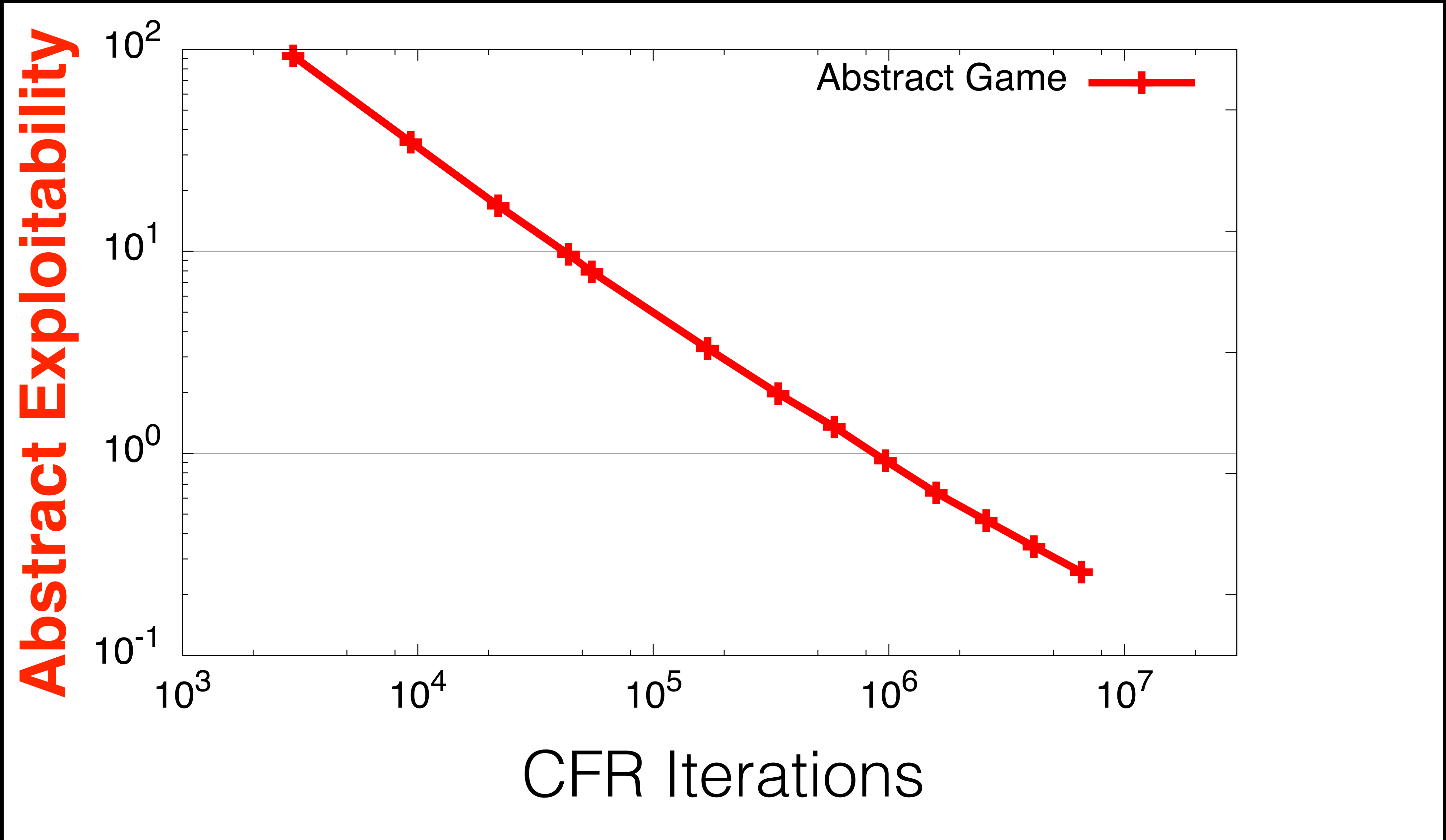


We'll just solve a big enough abstraction!



This was worrying… Flattening out already?

…But here's the overfitting effect:



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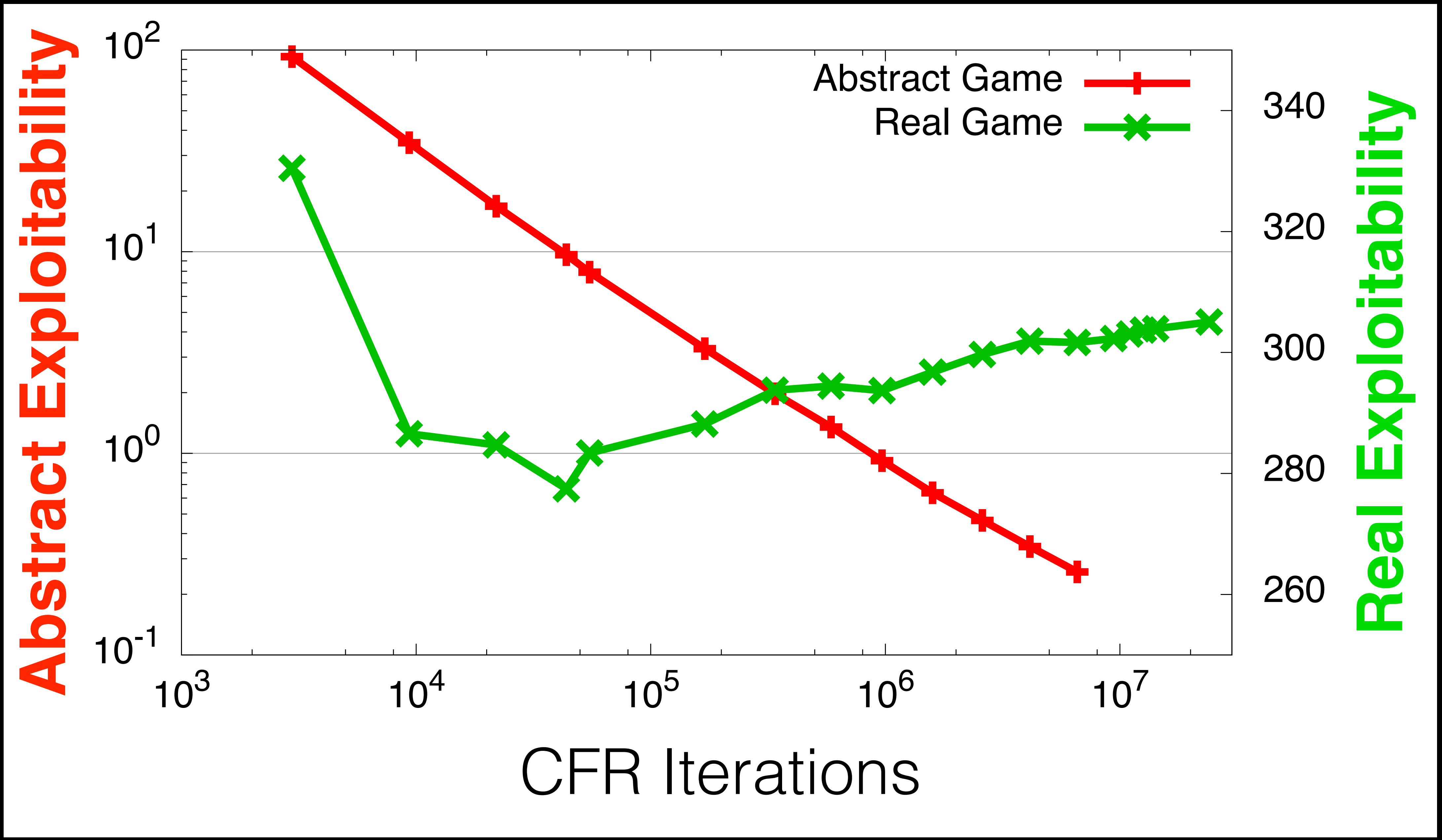

So: we’re far from solved,
and have a serious problem!

But we’re stuck with abstraction.

Can a different algorithm avoid overfitting?

Solving Attempt #2 (2012):

We'll solve a really big abstraction,
but *properly*,
so we don't overfit.

We’re solving a 2-player game.

If both players use abstraction, we overfit.

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If both players use abstraction, we overfit.

What if one player uses abstraction,
and their opponent doesn’t?

By definition, abstracted player
minimizes exploitability!

CFR-BR (AAAI 2012)

Normally, even one unobstructed player
would cost 262 TB of memory.

But we *can* do it without that much…
The 76-day best response computation does that!

Maybe if we run that in a loop…

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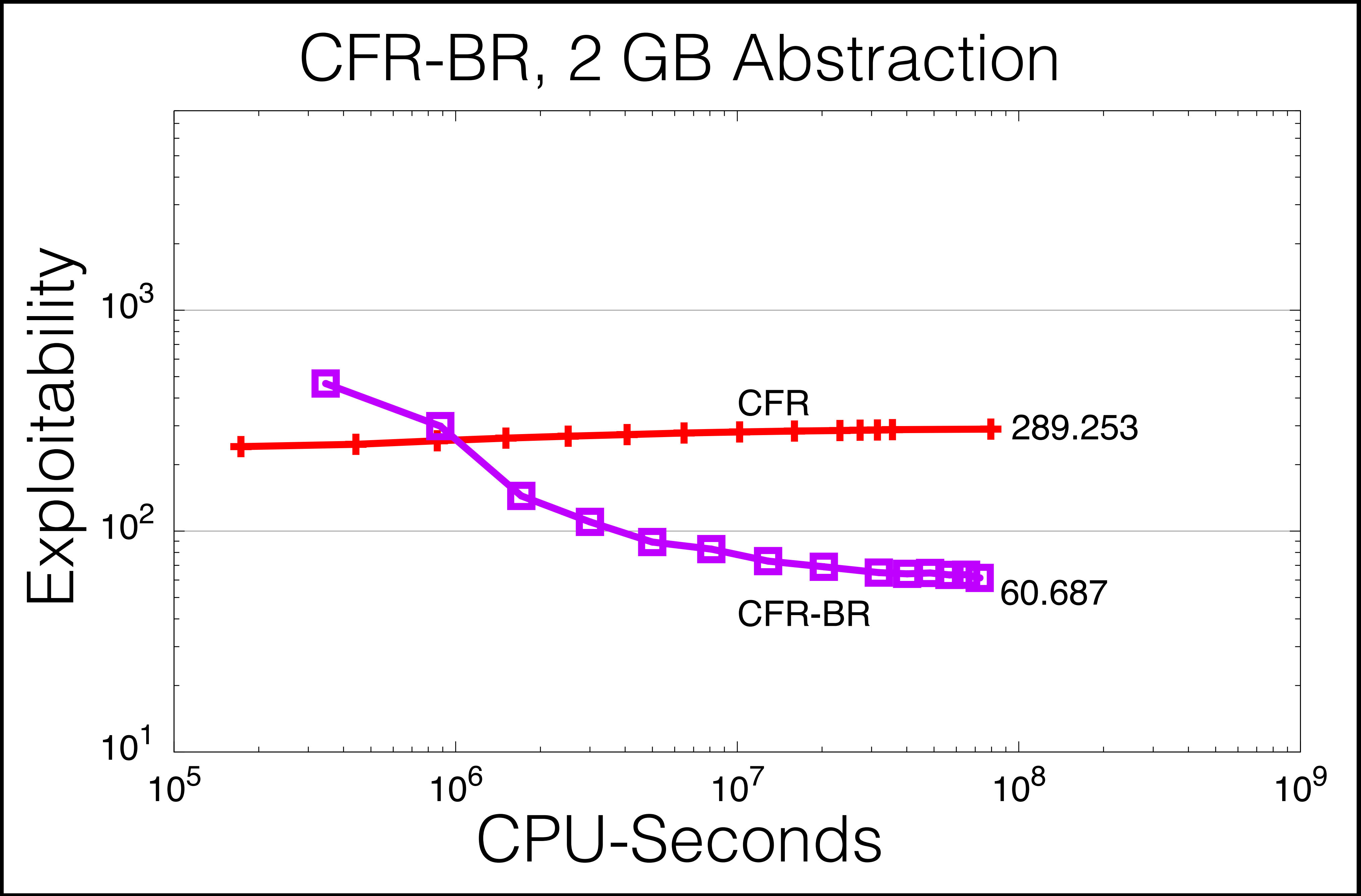
Normally, even one unobstructed player
would cost 262 TB of memory.

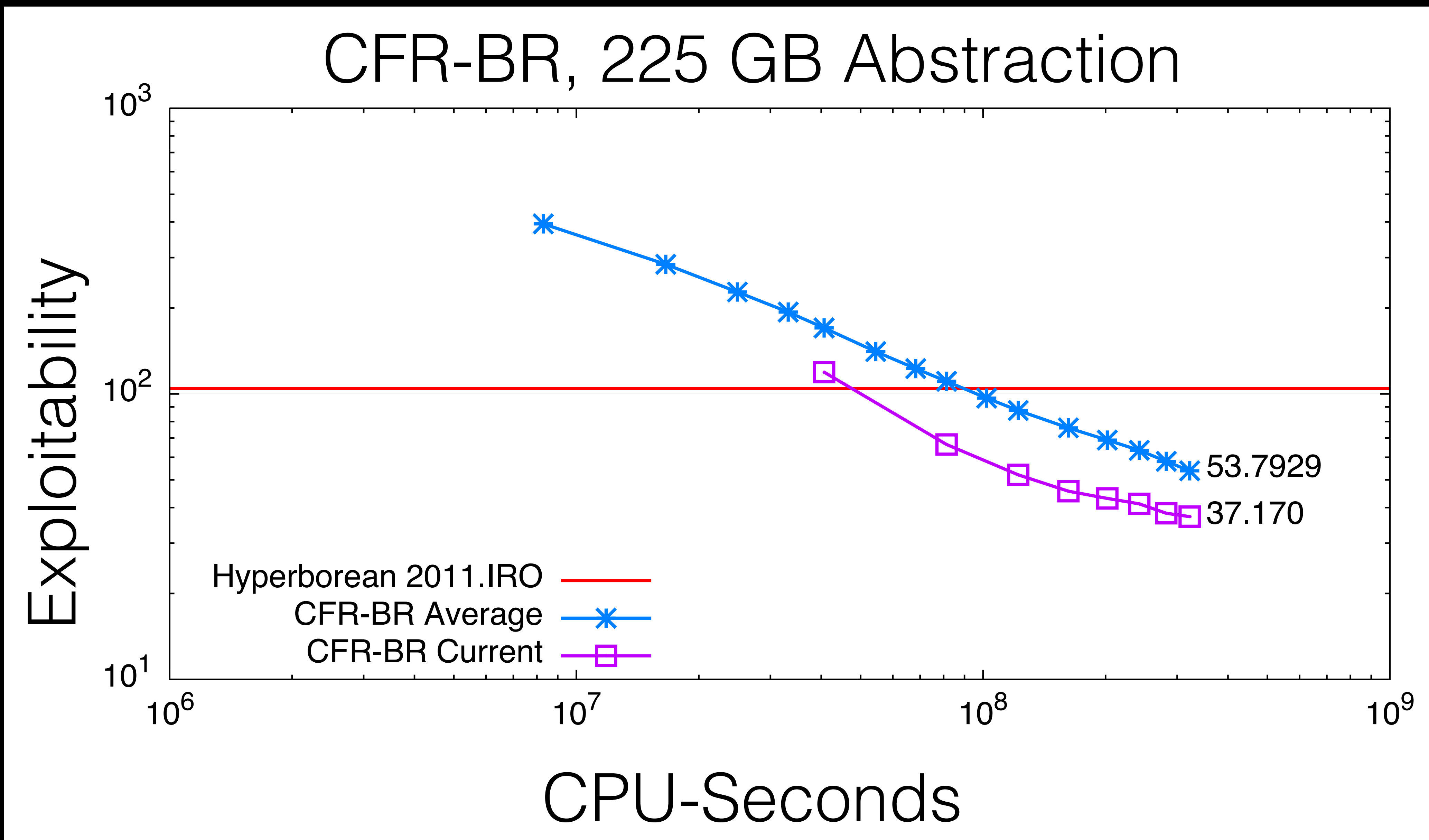
But we *can* do it without that much…
The 76-day best response computation does that!

Maybe if we run that in a loop… and use sampling
tricks to avoid the time cost… it's feasible!

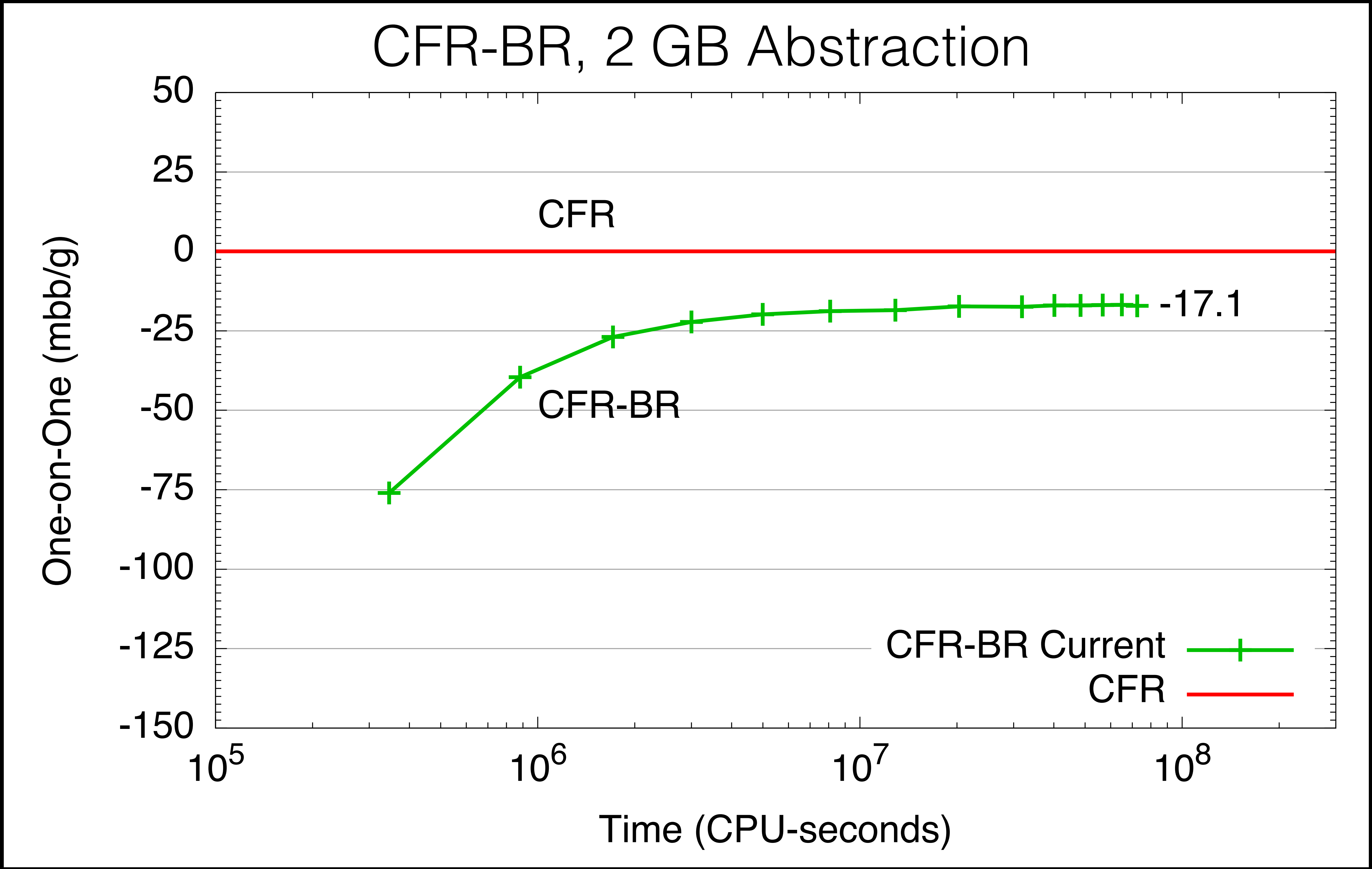
Promising results! CFR-BR has no overfitting, and is far less exploitable!
Small abstraction, but beat all previous strategies!



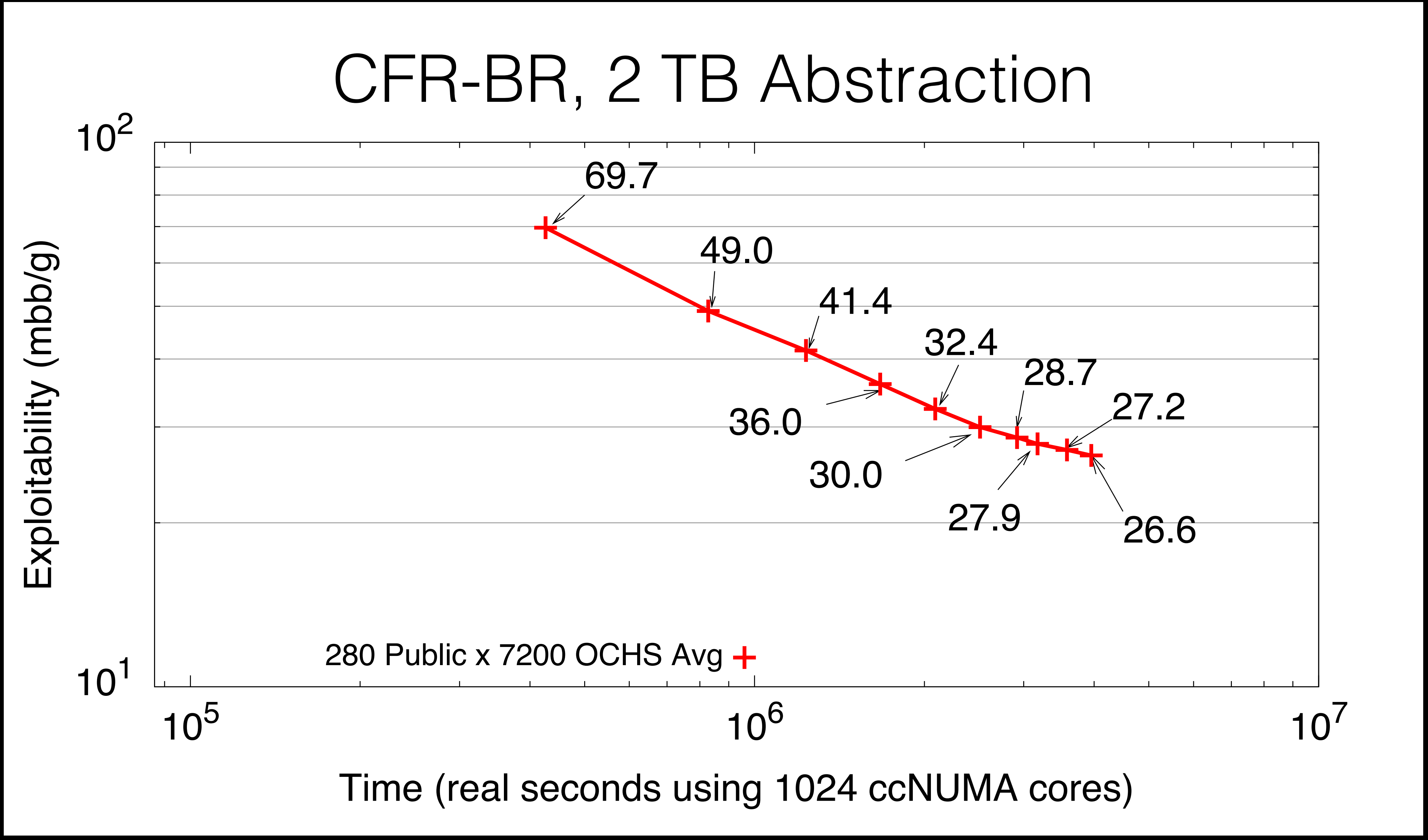
In a big strategy (225 GB to solve), we got closer to optimal than ever before.



However, CFR-BR *lost* in actual games.
Assuming opponent is stronger —> too pessimistic!

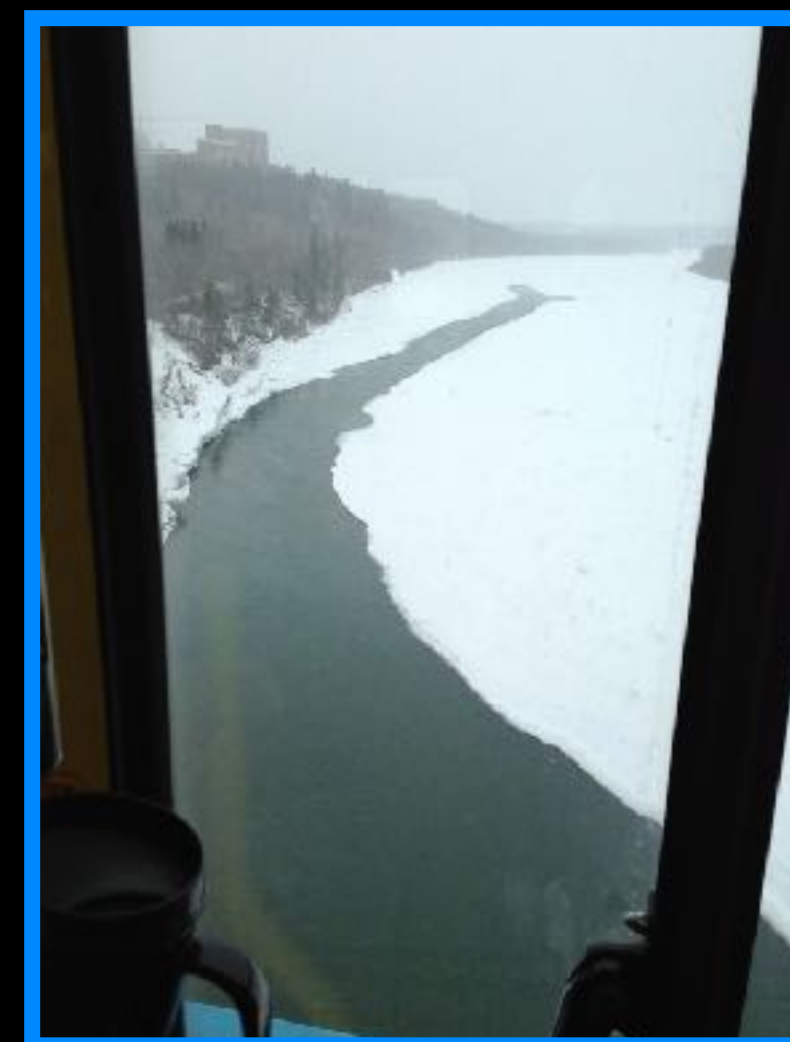


And still wasn't getting low enough:



That last strategy was computed on "Hungabee", an SGI UV 1000 in GSB. 16TB, 2048 cores.

North Saskatchewan River, -10C day



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Water cooling, heat dumped to river.

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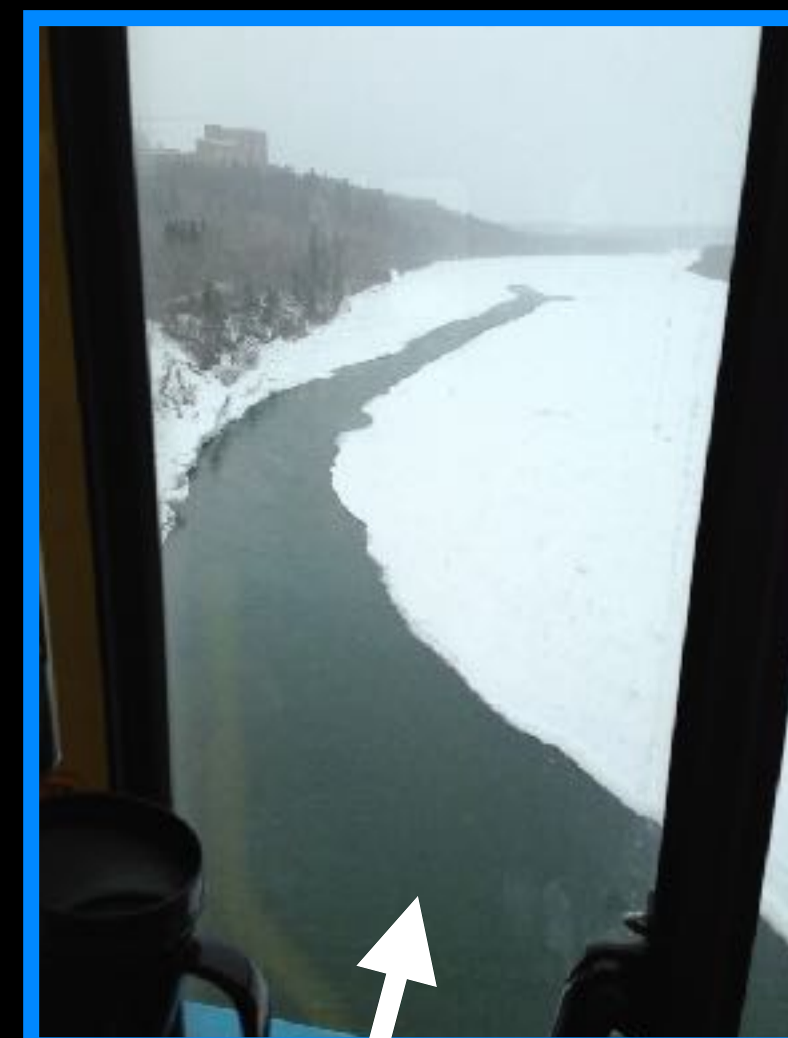


Program Output

Solving Attempt #3 (2013):

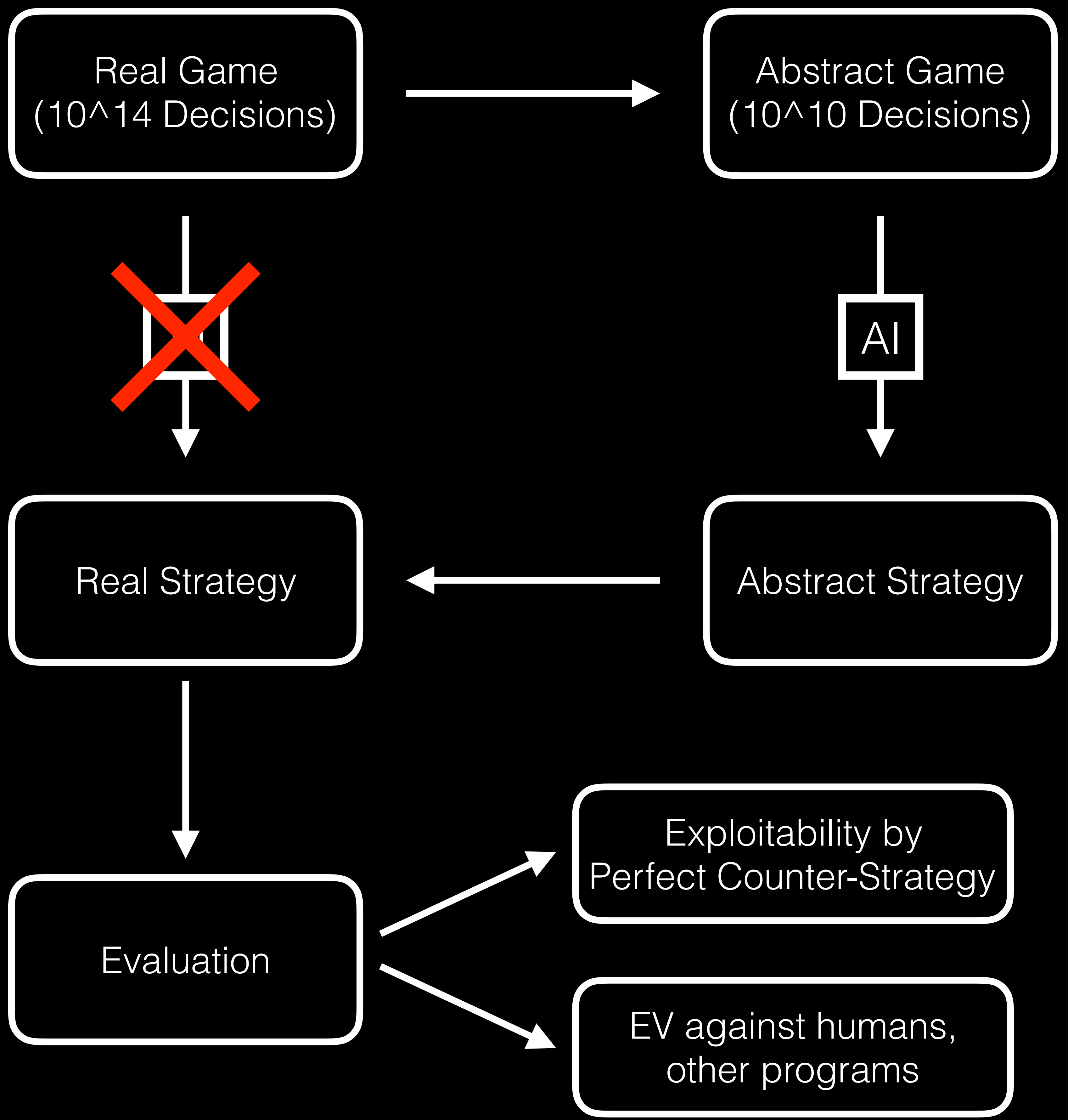
CFR-D: We'll avoid the memory cost
by solving game fragments as needed.

Watch for this in Neil Burch's upcoming thesis!

Flaw: ~16 GB instead of 523 TB of storage…
…but **massive** increase in CPU time required.

Finally:

Heads-Up Limit Texas Hold’em is Solved.
Science, 2015.



Hm. Abstraction is a dead end for perfection.

Was solving it directly *really* infeasible?

Old predictions:
Memory: 523 TB
CPU: ~10k years

In October 2013, our coauthor
Oskari Tammelin contacted us
with two ideas:

1

Poker-specific data compression.
523 TB —> 17 TB

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1. Poker-specific data compression.
523 TB —> 17 TB

2. CFR+. A new (at that time theoretically unproven) variant that converges **amazingly** quickly.
Key change: floor regret values at zero.

Third piece:
Massive resources from Compute Canada.

From our earlier attempts,
we had experience with large
distributed programs.

Third piece:
Massive resources from Compute Canada.

"Mammouth" cluster in Quebec.
We used 200 nodes,
24 cores/node. 4800 cores.

Each node had 32 GB RAM,
and 1 TB of local disk.

Each node handled a set of
subgames. Solve with
massive parallelism.

One last wrinkle: *Essentially* Solving a Game

Our algorithms converge towards optimal play in the limit.

“Solved” means unbeatable. We can only approximate it.
So how close is “close enough”?

One last wrinkle: *Essentially* Solving a Game

What if a human lifetime of play wasn't enough for someone to claim to beat our program?

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(200 games/hour) * (12 hours/day) * (70 years)
= 60 million games.

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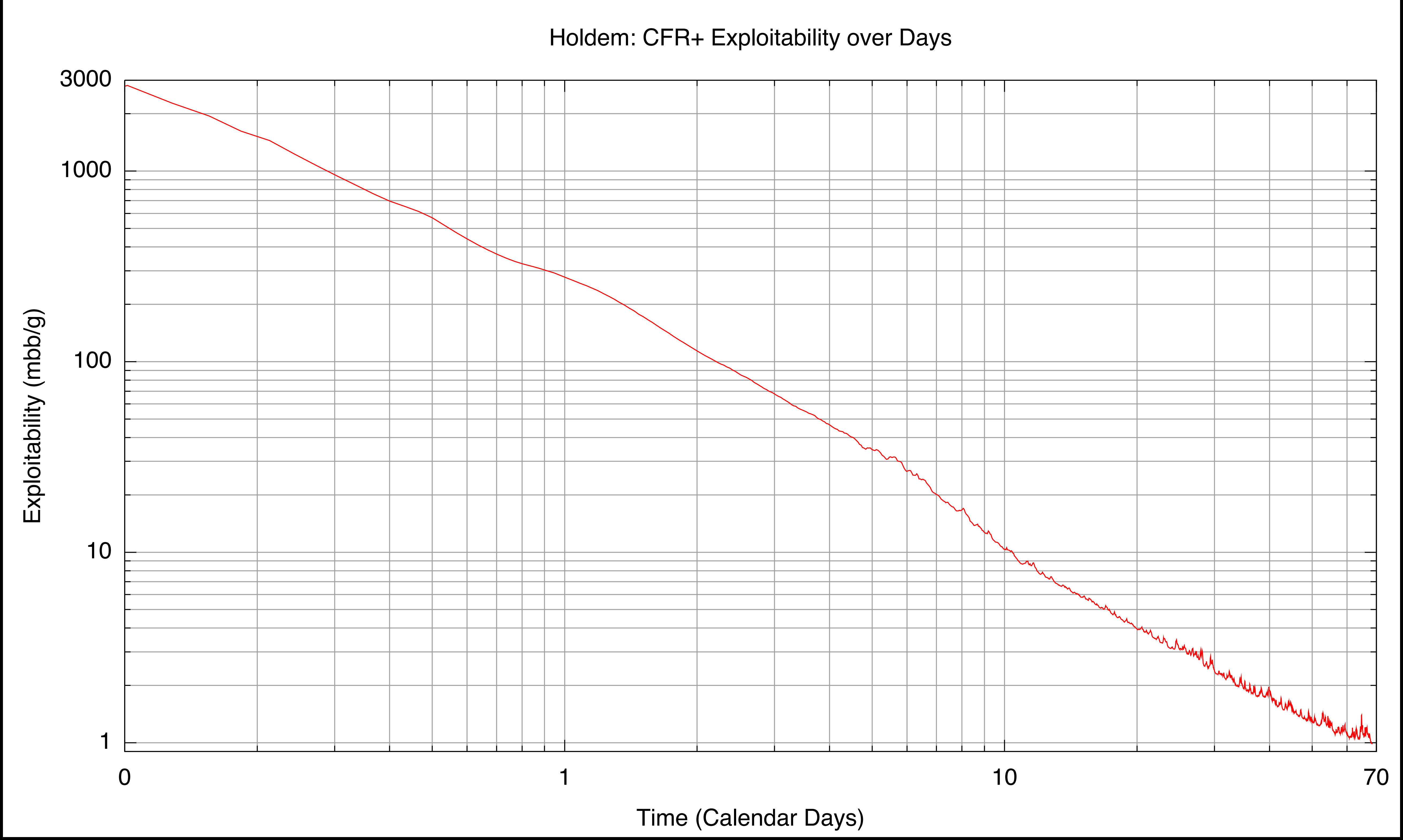
What if a human lifetime of play wasn't enough for someone to claim to beat our program?

(200 games/hour) * (12 hours/day) * (70 years) = 60 million games.

That isn't enough to discern "1 milli-big-blind" of exploitability with 95% confidence.
So that's our goal.

After 70 days (900 CPU-years), we reached 0.986 mbb/g. Essentially solved.



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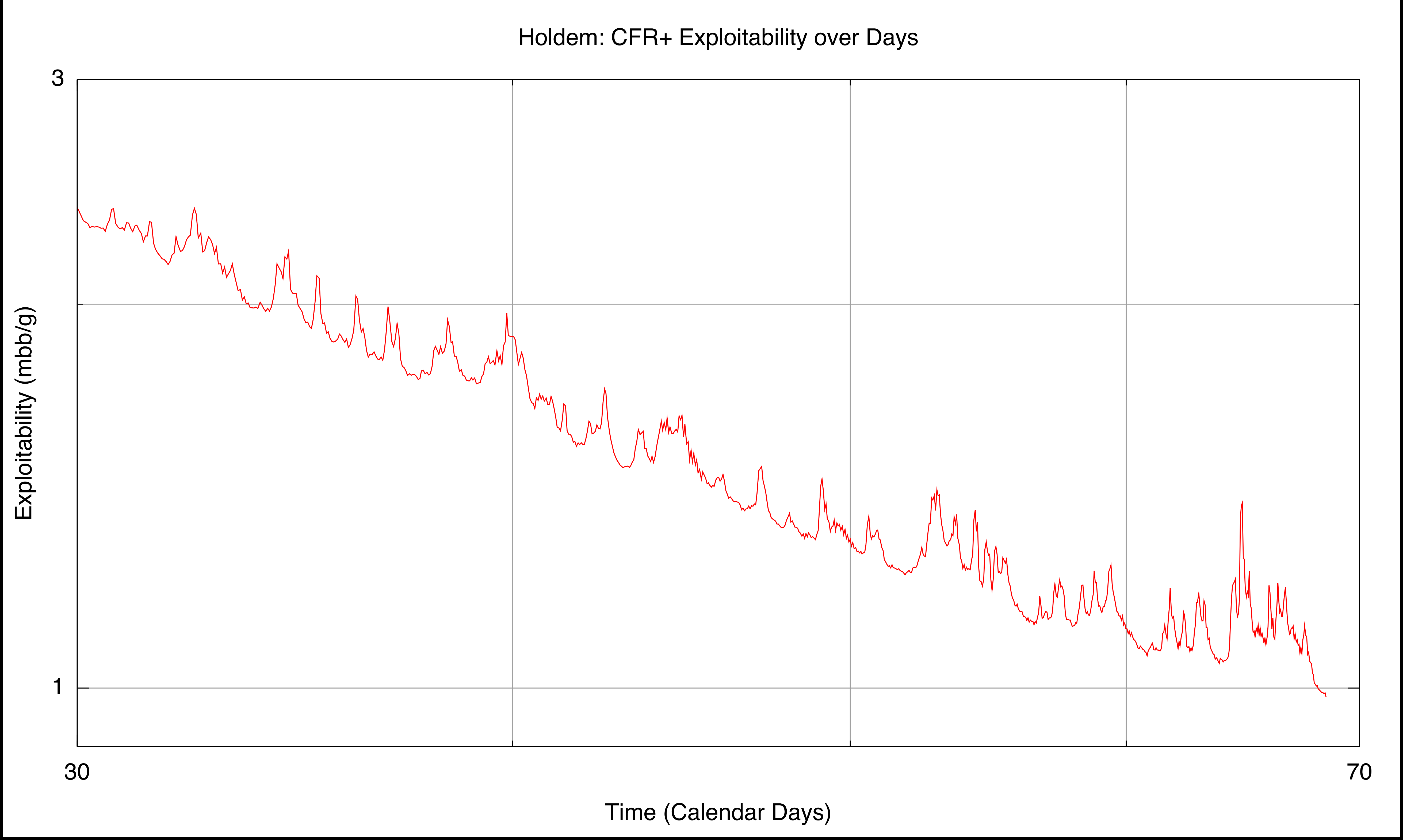
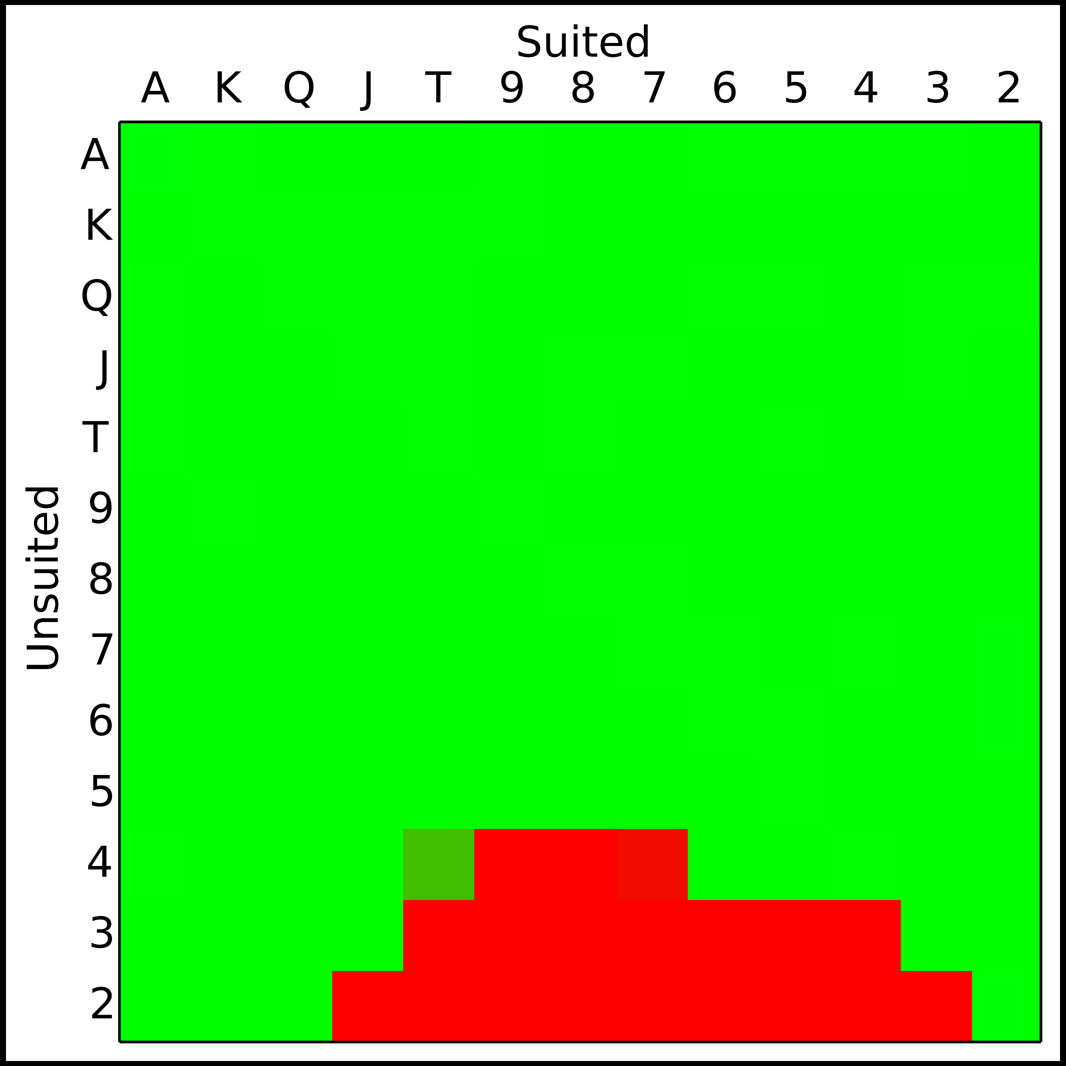
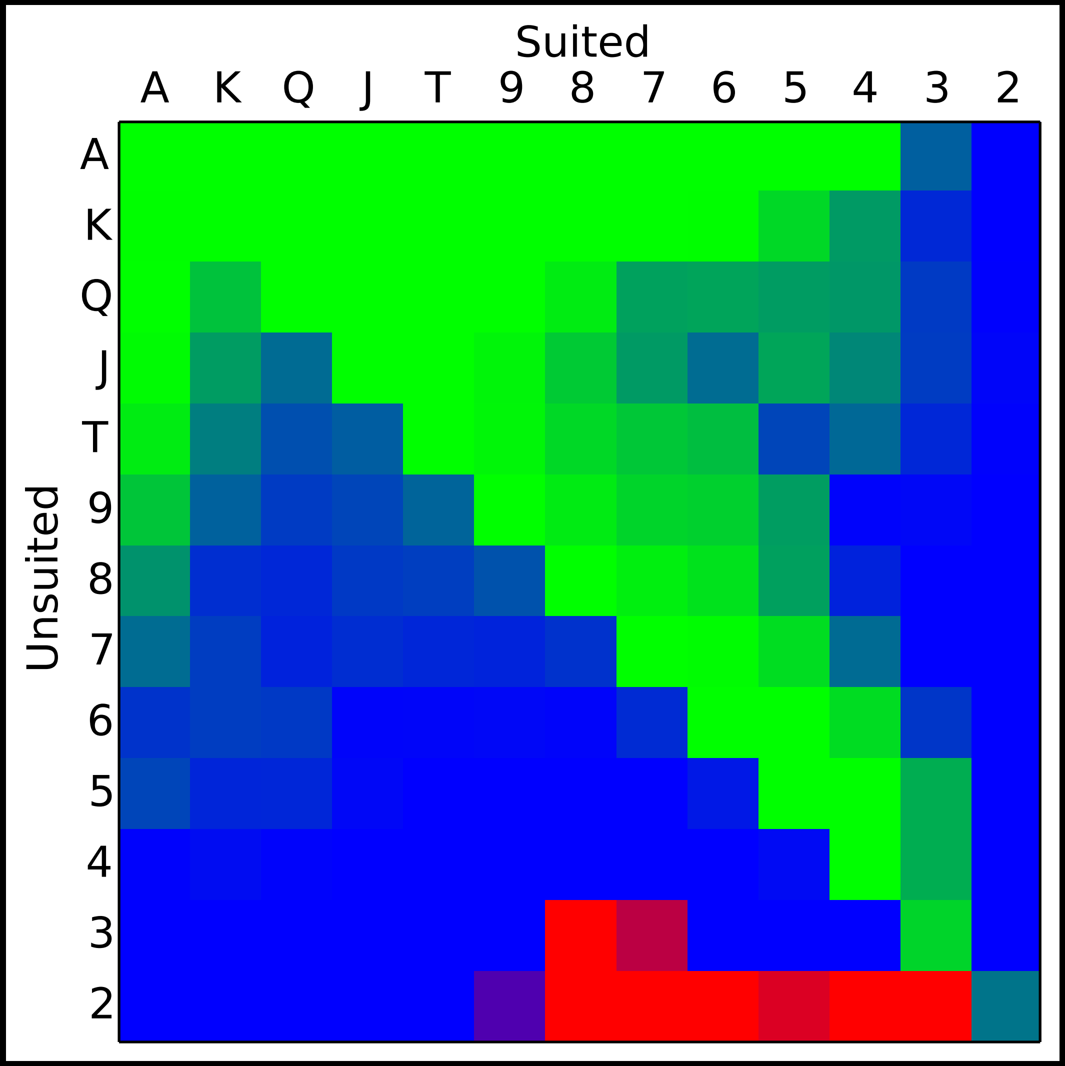


Game Start

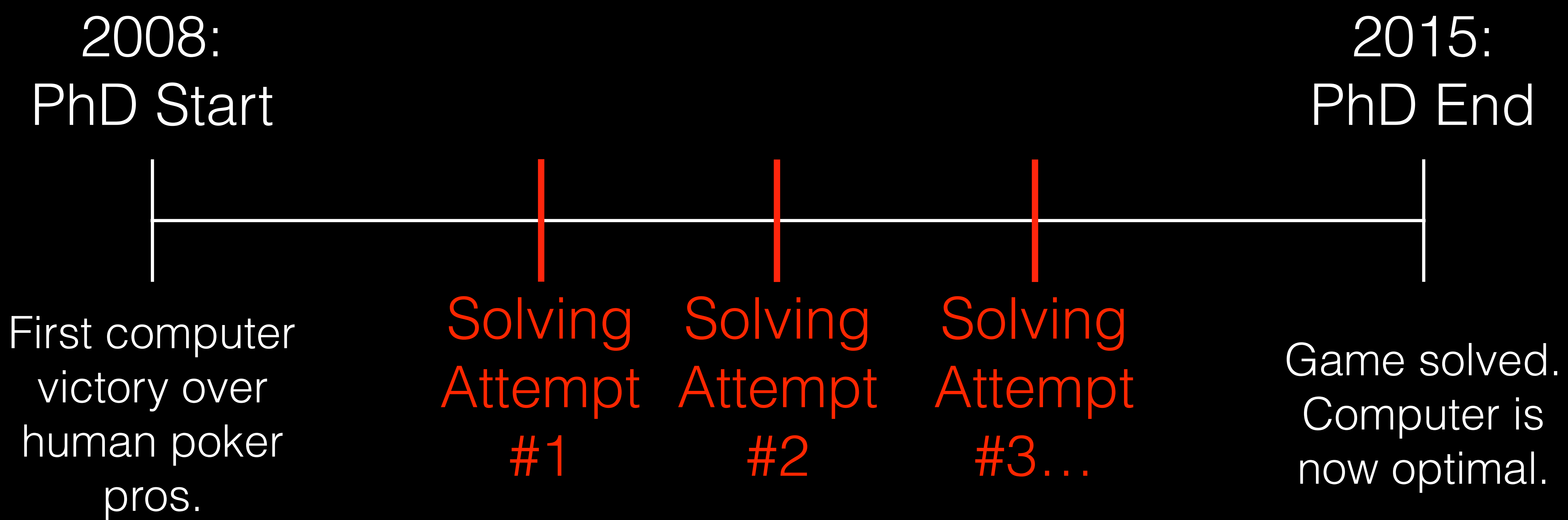


After a Raise



Play against it, inspect strategy, download the code:
http://poker.srv.ualberta.ca

Conclusion:



- My research spanned the End-to-End task of Abstraction-Solving-Translation

- Much easier to surpass humans than to be perfect!

- General set of tools: applicable to other games, and outside the games domain entirely.