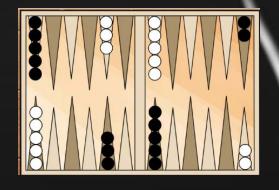


AI vs human



1992 Backgammon



1997 Chess



2016 Go



Challenges

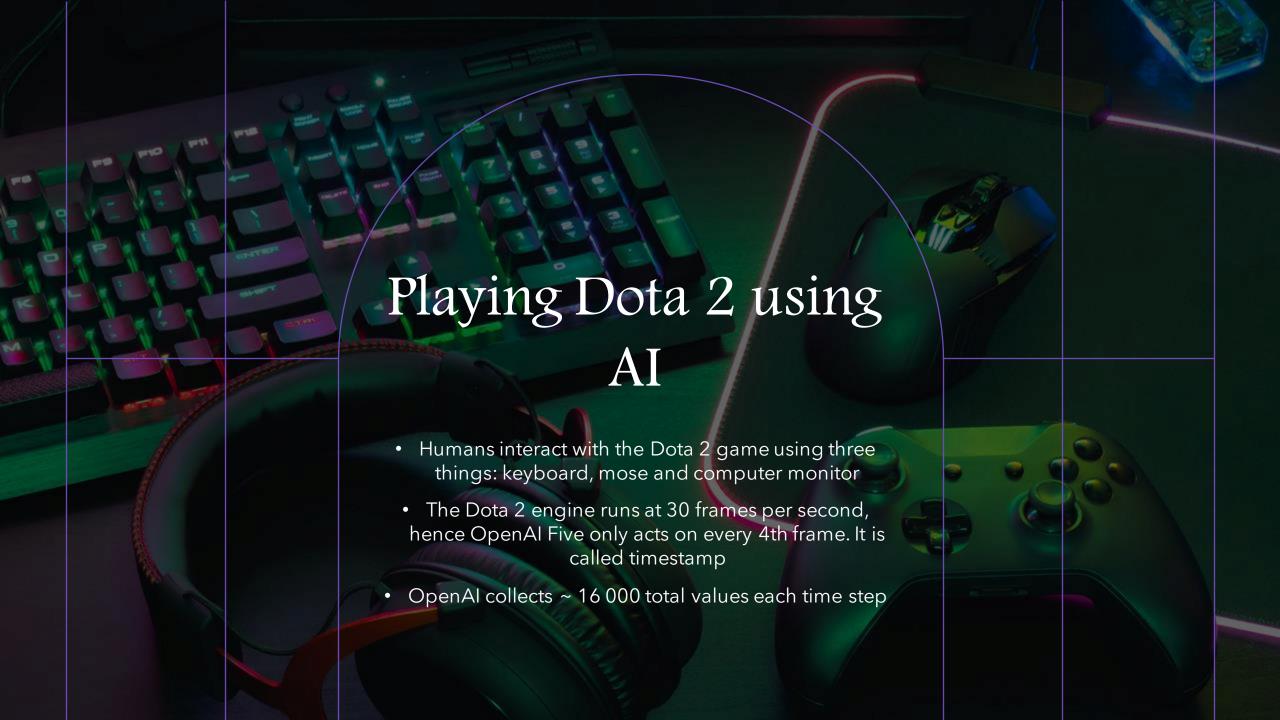
- Long time horizons.
- Partially-observed state.
- High-dimensional action and observation spaces.





Limitations

- Subset of 17 heroes
- No support for items which allow a player to temporarily control multiple units at the same time





Observation space

Global data				
time since game started	1			
is it day or night?				
time to next day/night change	2			
time to next spawn: creep,	4			
neutral, bounty, runes				
time since seen enemy courier				
is that > 40 seconds? ^a	2			
min&max time to Rosh spawn	2			
Roshan's current max hp	1			
is Roshan definitely alive?	1			
is Roshan definitely dead?	1			
Next Roshan drops cheese?	1			
Next Roshan drops refresher?	1			

Per-hero add'l (10 heroes)	25
is currently alive?	1
number of deaths	1
hero currently in sight?	
time since this hero last seen	2
hero currently teleporting?	
if so, target coordinates (x, y)	
time they've been channeling	4
respawn time	1
current gold (allies only)	1
level	1
mana: max, current, & regen	3
health regen rate	1
magic resistance	1

Per-modifier (10 heroes x 10 modifiers & 179 non- heroes x 2 modifiers)	2
remaining duration	1
stack count	1
modifier name	1
Per-item (10 heroes x 16	13

Per-item (10 heroes x 16	13
items)	
location one-hot (inven-	3
tory/backpack/stash)	
charges	1
is on cooldown?	
cooldown time	2
is disabled by recent swap?	

Reward weights

	D 1		l B
Name	Reward	Heroes	Description
Win	5	Team	
Hero Death	-1	Solo	
Courier Death	-2	Team	
XP Gained	0.002	Solo	
Gold Gained	0.006	Solo	For each unit of gold gained. Reward is not lost
			when the gold is spent or lost.
Gold Spent	0.0006	Solo	Per unit of gold spent on items without using
			courier.
Health Changed	2	Solo	Measured as a fraction of hero's max health. [‡]
Mana Changed	0.75	Solo	Measured as a fraction of hero's max mana.
Killed Hero	-0.6	Solo	For killing an enemy hero. The gold and expe-
			rience reward is very high, so this reduces the
			total reward for killing enemies.
Last Hit	-0.16	Solo	The gold and experience reward is very high, so
			this reduces the total reward for last hit to ~ 0.4 .
Deny	0.15	Solo	
Gained Aegis	5	Team	
Ancient HP Change	5	Team	Measured as a fraction of ancient's max health.
Megas Unlocked	4	Team	
T1 Tower*	2.25	Team	
T2 Tower*	3	Team	
T3 Tower*	4.5	Team	
T4 Tower*	2.25	Team	
Shrine*	2.25	Team	
Barracks*	6	Team	
Lane Assign [†]	-0.15	Solo	Per second in wrong lane.

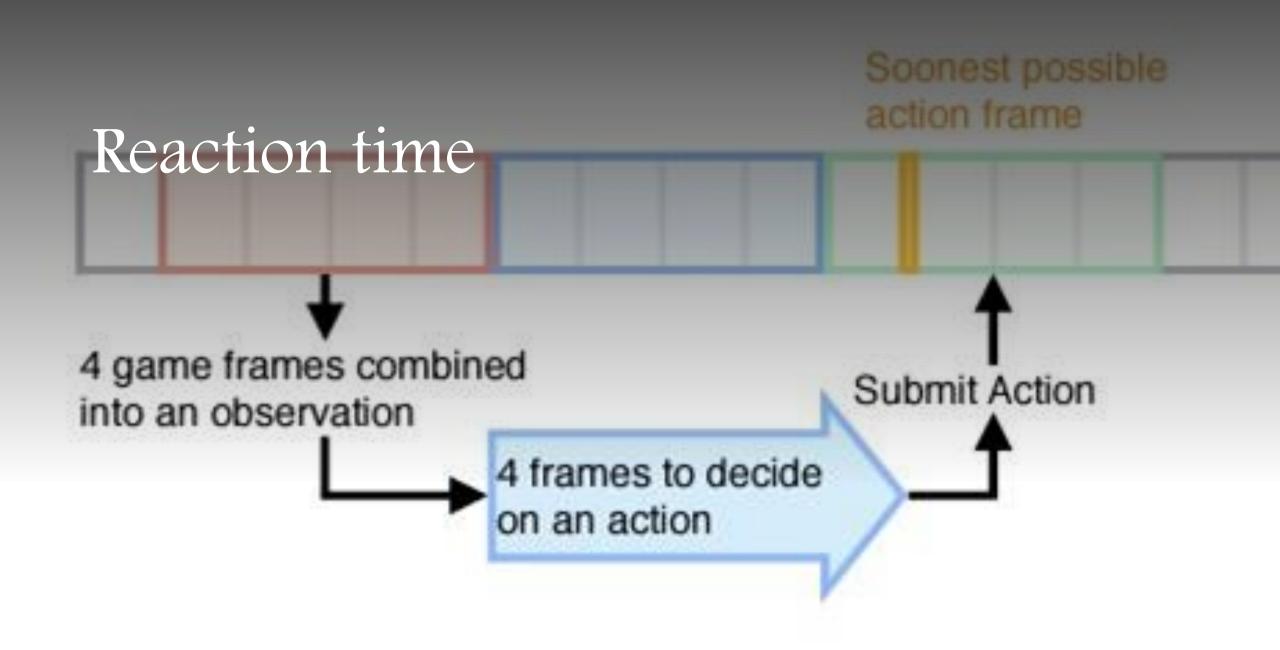
Game time weighting

$$\rho_i \leftarrow \rho_i \times 0.6^{(T/10 \text{ mins})}$$

Team spirit

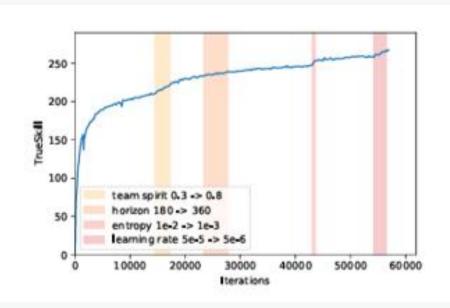
$$r_i = (1 - \tau)\rho_i + \tau \overline{\rho}$$





Hyperparameter changes over time and optimizing the policy

Learning Rate	5e-5			5e-6	
Entropy coefficient	0.01		ii .	0.001	
GAE Horizon	180 secs		360 s	360 secs	
Team Spirit	0.3	0.8			
TrueSkill	0	210	232	245	258
Time (days)	0	13	20	33	42
Iteration	0	15k	23k	43k	54k





Can u beat it?

Opponent	Result	Duration	Version	Restrictions			
June 6, 2018 - Internal Event							
Internal team	win	15:15 (surr)	7.13	Mirror match, multiple couriers, no invis			
Internal team	win	20:51	7.13	Mirror match, multiple couriers, no invis			
Audience team	win	31:33	7.13	Mirror match, multiple couriers, no invis			
Audience team	win	23:33 (surr)	7.13	Mirror match, multiple couriers, no invis			
August 5, 2018 - Benchmark							
Caster team	win	21:38 (surr)	7.16	Drafted, multiple couriers			
Caster team	win	24:56 (surr)	7.16	Drafted, multiple couriers			
Caster team	lose	35:47	7.16	Audience draft, multiple couriers			
August 9, 2018 - 1	Private e	val					
Team Secret	win	17:00 (surr)	7.16	Drafted, multiple couriers			
Team Secret	lose	48:46	7.16	Drafted, multiple couriers			
Team Secret	lose	38:55	7.16	Drafted, multiple couriers			
August 22-23, 2018 - The International							
Pain Gaming	lose	52:29	7.19	Pre-set lineup			
Chinese Legends	lose	45:44	7.19	Pre-set lineup			
October 5, 2018 - Private eval							
Team Lithium	win	48:57	7.19	TI pre-set lineup			
Team Lithium	win	48:16	7.19	TI pre-set lineup			
Team Lithium	win	31:33	7.19	Drafted			
January 16, 2019 - Private eval							
SG Esports	win	24:29 (surr)	7.19	TI pre-set lineup			
SG Esports	win	25:08 (surr)	7.19	Drafted			
SG Esports	win	27:36 (surr)	7.20	Mirror match			
SG Esports	win	25:30 (surr)	7.20	Mirror match			
February 1, 2019	February 1, 2019 - Private eval						
Alliance	win	17:11	7.20d	Drafted			
Alliance	win	31:33	7.20d	Drafted			
Alliance	win	28:16	7.20d	Reverse drafted			
April 13, 2019 - C	penAl F	ive Finals					
OG	win	38:18	7.21d	Drafted			
$^{ m OG}$	win	20:51	7.21d	Drafted			

Table 7: Major matches of OpenAI Five against high-skill human players.



Human Evaluation

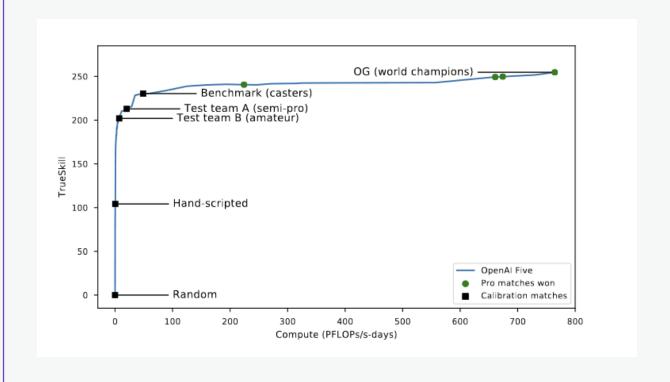


OpenAl Five pokonało mistrzów świata 13 kwietnia 2019



18-21 kwietnia OpenAl Five Arena

TrueSkill



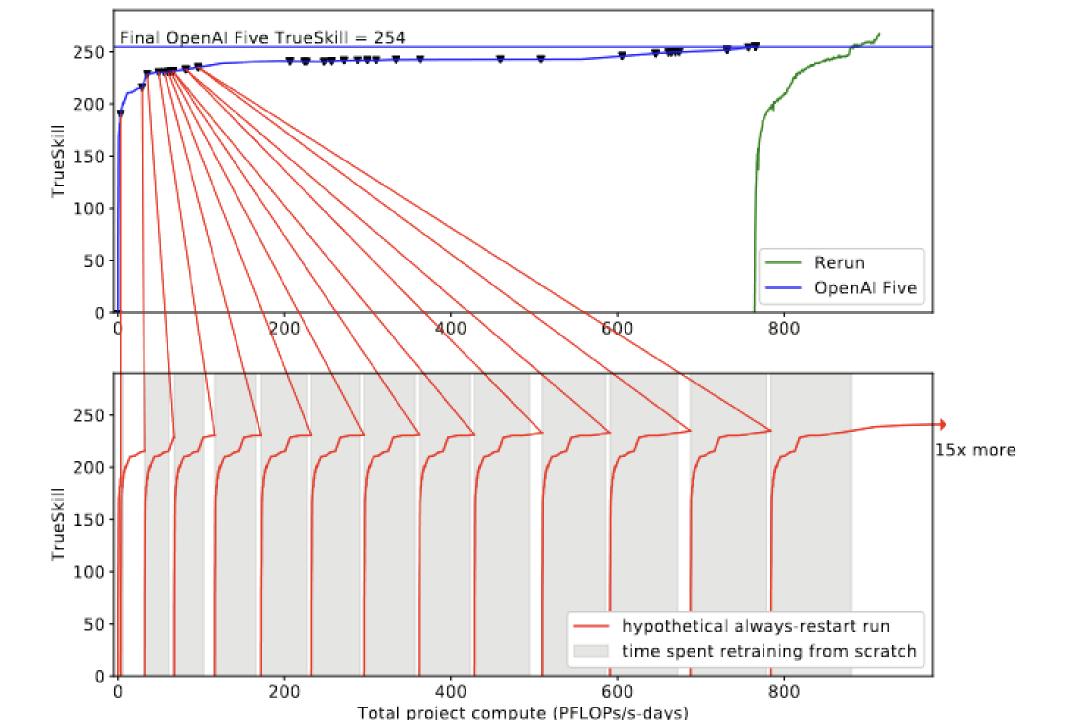
Playstyle

Na początku unikalny, miał swoje wady

Z czasem był bardziej ludzki ale nadal miał unikalne dla siebie zachowania

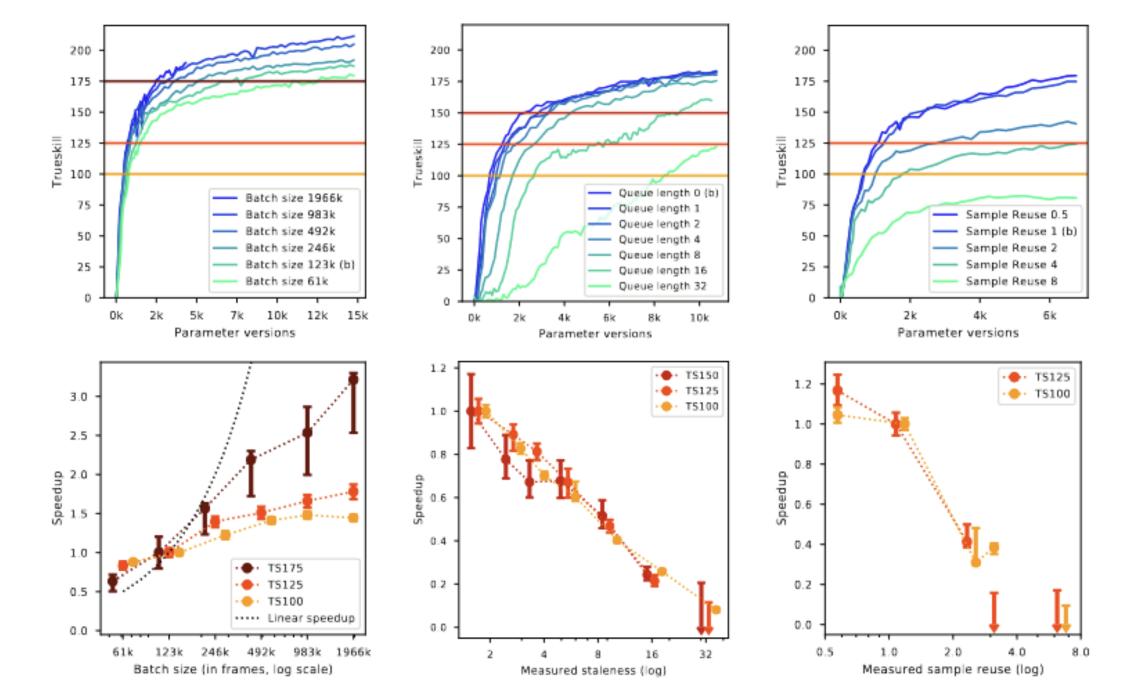
Validating surgery with rerun

- Rerun trwał 2 miesiące
- Jeżeli zamiast surgery wykonywany był restart uczenia, Al uczyło by się 40 zamiast 10 miesięcy
- Rerun miał 98% win rate z OpenAl Fice
- Surgery jest potencjalnie do poprawienia, gdyż rerun osiąga wyższy TS



Batch size

- Zwiększenie liczby GPU oraz liczby rollout machines
- Pożądany speedup spowodowany zwiększaniem batch size jest liniowy
- Liniowy speedup nie został osiągnięty, jednak był on znaczący



Data Quality



Około 2h trwania jednej gry powoduje problemy podczas uczenia



Twórcy użyli podejścia asynchronicznego w procesie uczenia

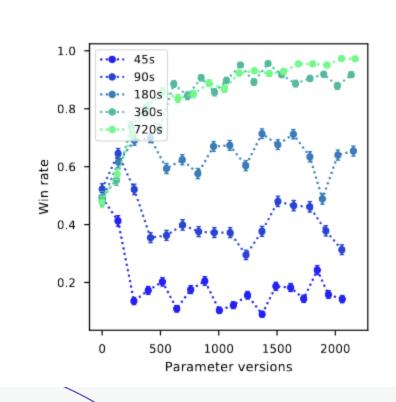


Pojawiły się problemy staleness i sample reuse

Long term credit assignment

- Dota 2 ma bardzo długi czas zależności między ruchami
- Time horizon

$$H = \frac{T}{1 - \gamma}$$



Podsumowanie

- OpenAl Five osiągnęło nadludzki poziom w grze Dota2
- Kluczowym składnikiem było zwiększenie batch size'u oraz czasu uczenia z użyciem surgery
- Możliwe, że rezultaty mogą być przełożone na inne gry
- Wraz ze zwiększaniem się złożności problemów i środowisk skalowanie będzie jeszcze ważniejsze

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- Andrew Trask, "Deep Learning from Scratch: Building with Python from First Principles", O'Reilly Media, 2019.

