

Autonomous Agents for Complex Simulations: A Compute-Efficient Imitation Learning Approach

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modl.ai

What am I doing here?

Constructing Human-like Agents for Complex Systems

- ▶ Many complex simulations (socio-technical systems) require human-like agents
 - Opponents, team-mates, instructors, etc.
- ▶ These could be constructed in various ways:
 - Elaborate manual construction (labor-intensive)
 - Reinforcement learning (not very human-like)
 - Imitation learning
- ▶ Many constraints
 - Data, training time, inference time

Tactical First-Person Shooters

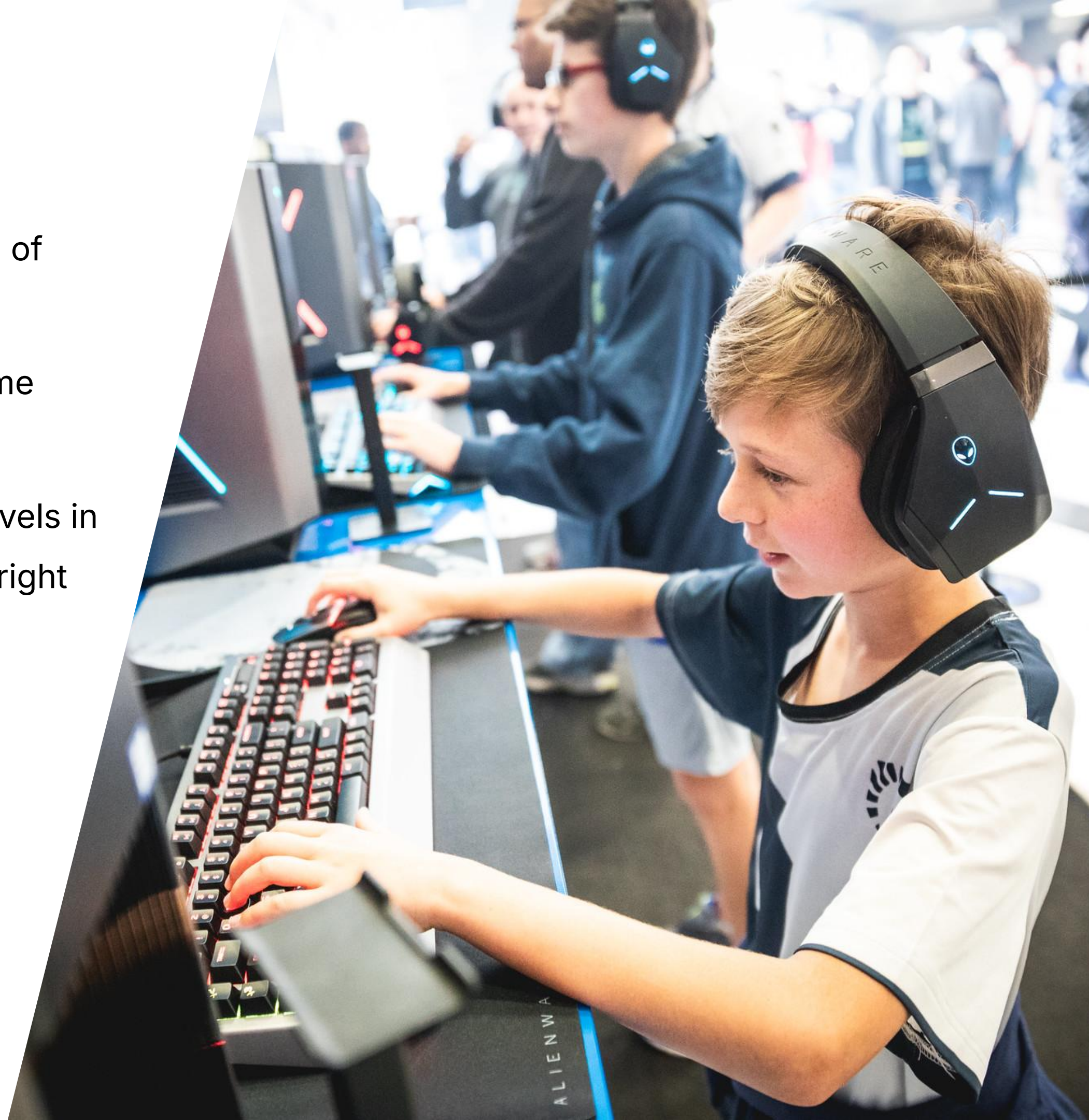


The Mission

Demonstrate Human-like bots for use as teammates and opponents
in a Tactical FPS game

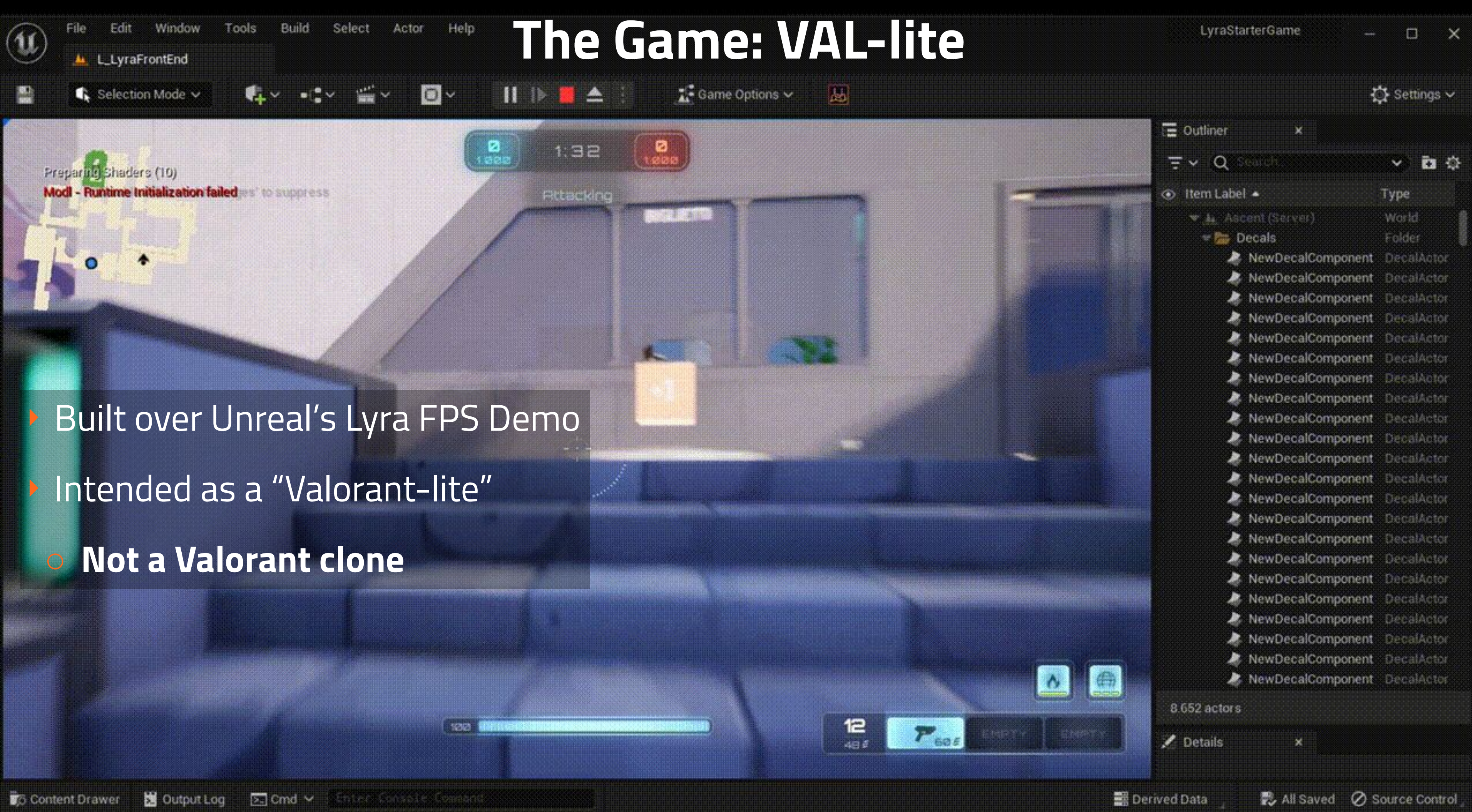
Using ML to Create Agents

- Our agents learn from human players instead of relying solely on scripted behavior
- Minimize AI programmer upkeep costs at game updates
- Can train different agents for different skill-levels in the player base and challenge players at the right level



The Game: VAL-lite

- ▶ Built over Unreal's Lyra FPS Demo
- ▶ Intended as a "Valorant-lite"
- **Not a Valorant clone**



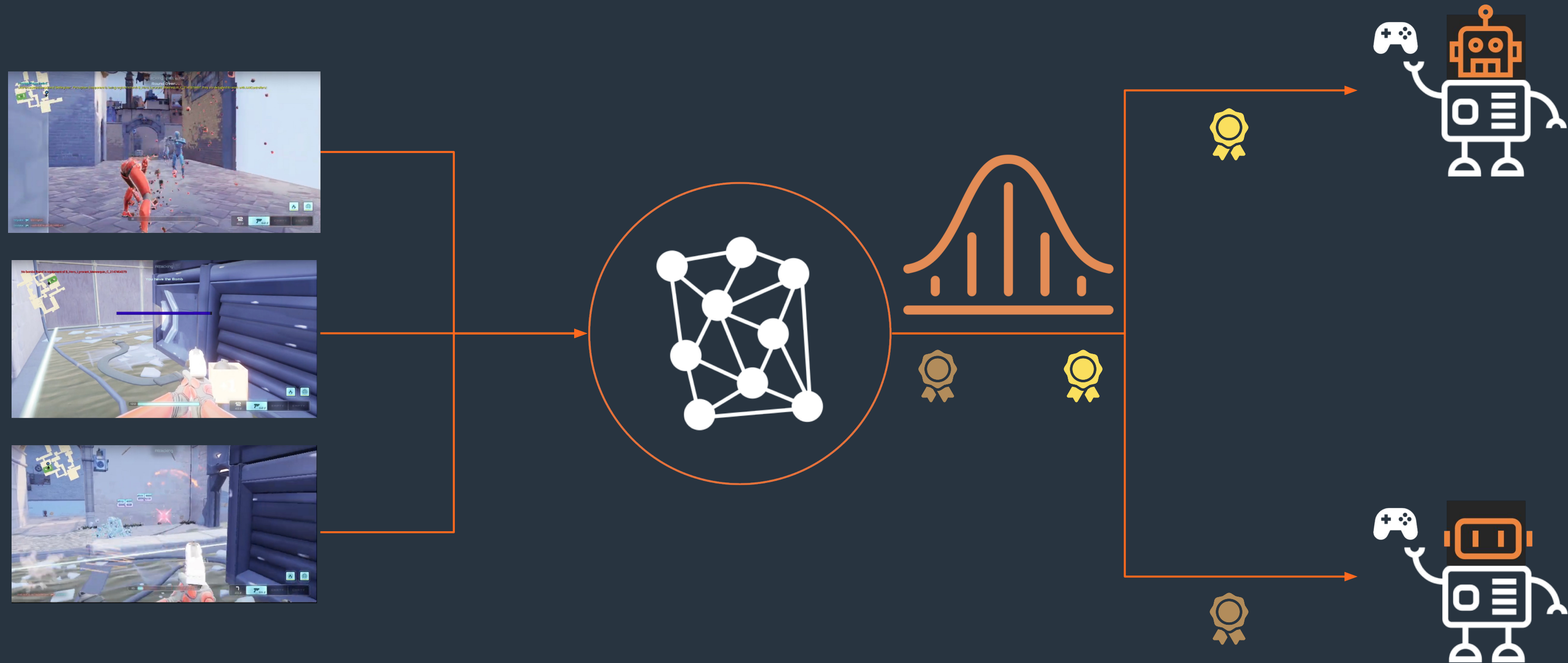
Core VAL-Lite Features

- ▶ 2v2 team gameplay
 - ▶ 2 characters based on the **Initiator** and **Controller** roles in Valorant
 - ▶ Bomb-planting game mode
 - ▶ Simplified version of **Ascent** map
 - 1 bomb site
 - Removed some areas from map
 - ▶ 1 weapon (Pistol)
- ▶ **Initiator** character has:
 - A blinding grenade
 - An ability suppression grenade
 - Inspired by **KAY/O**
 - ▶ **Controller** character has:
 - An incendiary grenade
 - A smokescreen/sphere grenade
 - Inspired by **Brimstone**

Some Constraints

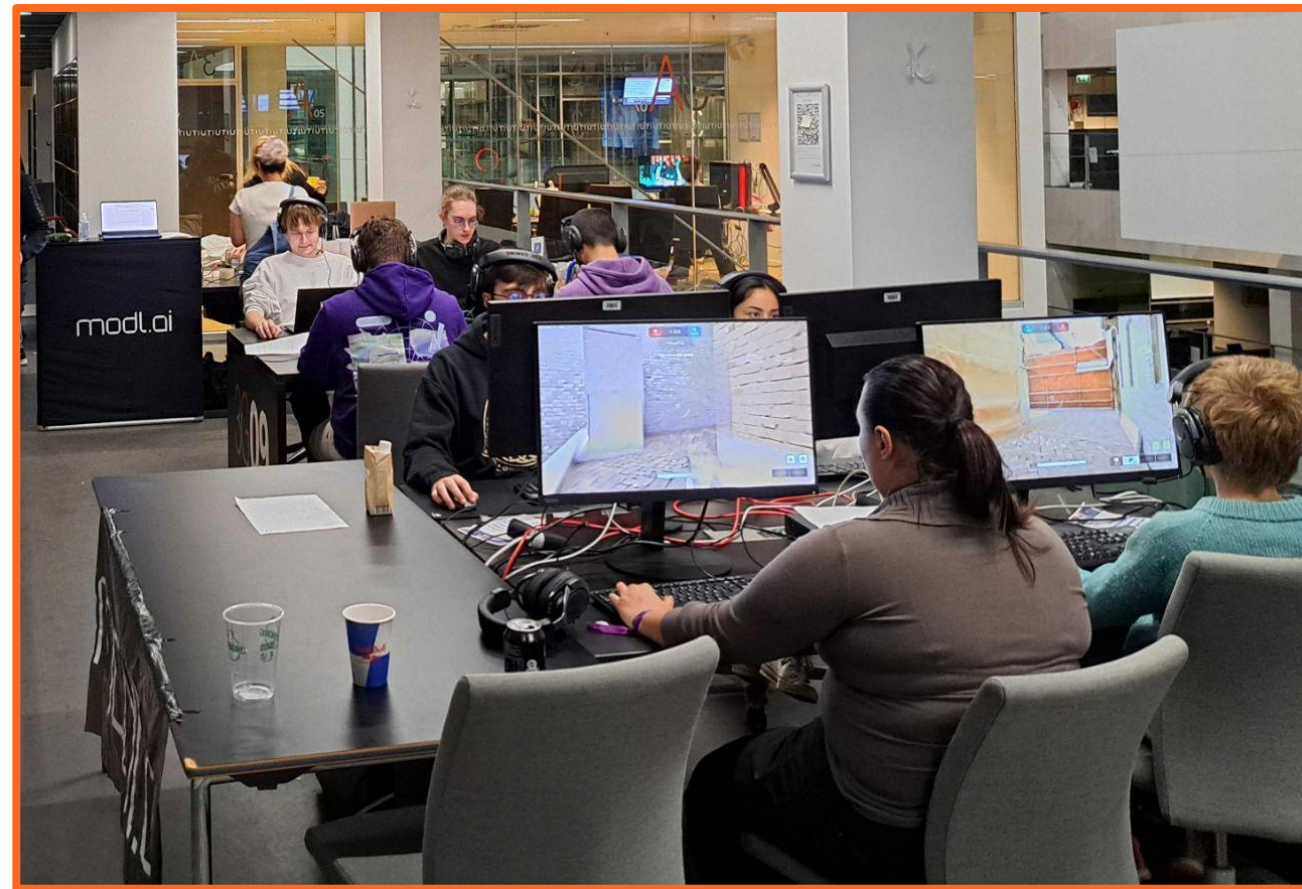
- ▶ Inference needs to fit inside the core game update loop
 - A few milliseconds at most
- ▶ Needs to work on servers without a GPU
 - Inference on CPU
 - Ideally, should fit into CPU cache
 - Pixels? Fuhgeddaboutit
- ▶ Should work with a variety of different playing styles
- ▶ Ideally, architecture and sensors should transfer to other similar games

Using ML to Create Bots



How we did it: Data

- ▶ Collected gameplay data from players
 - Relatively wide skill range
 - Allows us to tailor bot skill
- ▶ No pixels! Only sensors (see later slide)
 - Deployable cheaply in production
- ▶ Possible agent behaviors, strategies, skill levels, and adaptations scale with the available data
- ▶ More data = better and more diverse agents
 - Currently trained on <50 hours of play time

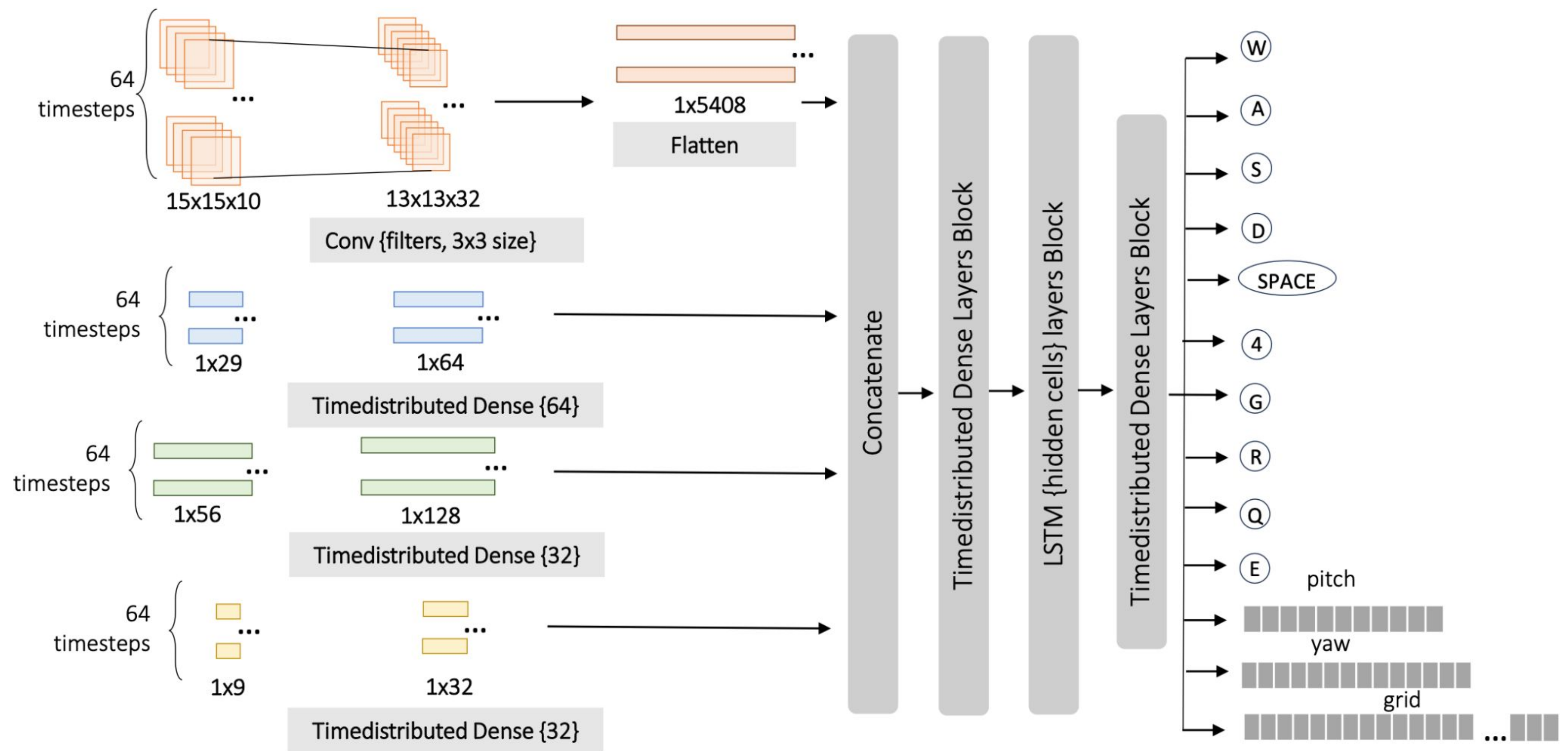


Agents in action



Model Architecture Details

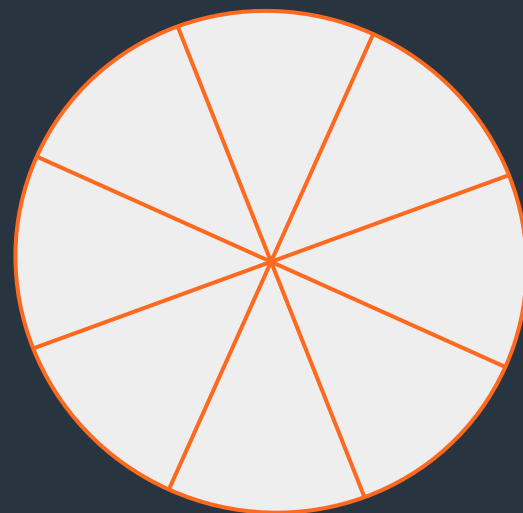
- ▶ Convolutional LSTMs
- ▶ 64 time-steps
- ▶ 4 input streams:
 - State features
 - Sensor grids
 - Audio sensors
 - Directional and distance features
- ▶ 2 LSTM layers -> 1 Dense layer
- ▶ ~24.5 million parameters
- ▶ Base model trained for ~300 epochs
- ▶ Expert and Novice models fine-tuned for ~250
 - On top and bottom 75% of data
- ▶ Full model trained for another ~1000
 - On full data set



Sensors

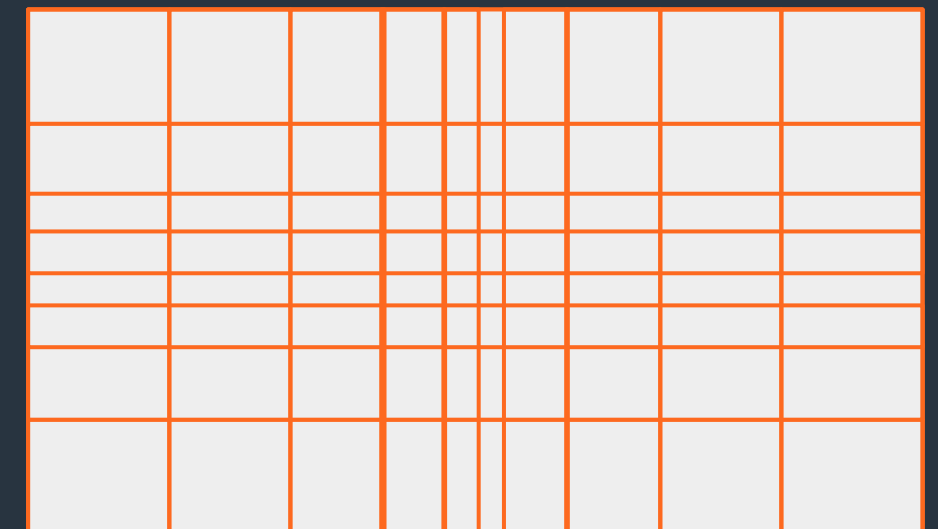
▶ Audio (directional)

- Distance to source
- **Shots fired**
- **Footsteps**
- **Grenade bouncing**
- **Grenade exploding**
- **Bomb beeping**



▶ Visual (15x15 sensors for each)

- Concentrated around center
- **Walls**
- **Enemies**
- **Teammate**
- **Bomb (dropped, planted)**
- **Grenade (team, enemy)**
- **Bombsite**
- **Smoke**
- **Incendiary**



Sensors, visualized

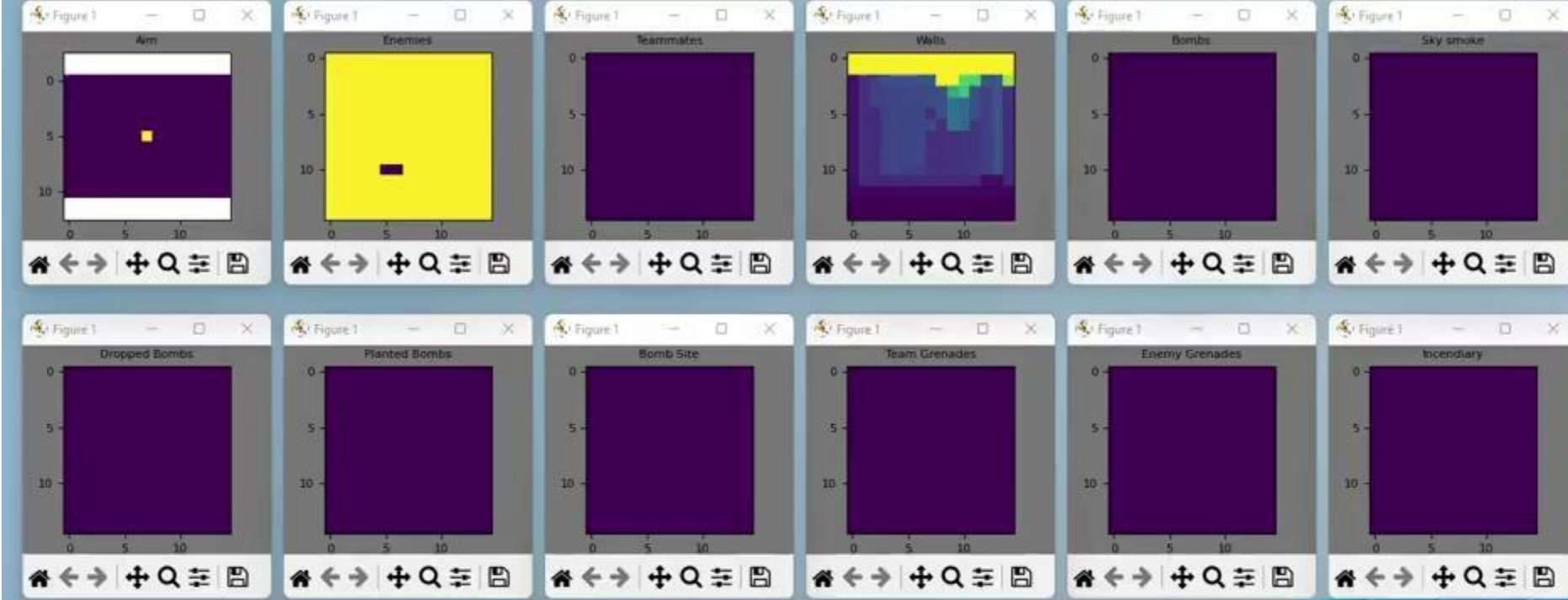


(a) Horizontal rays.



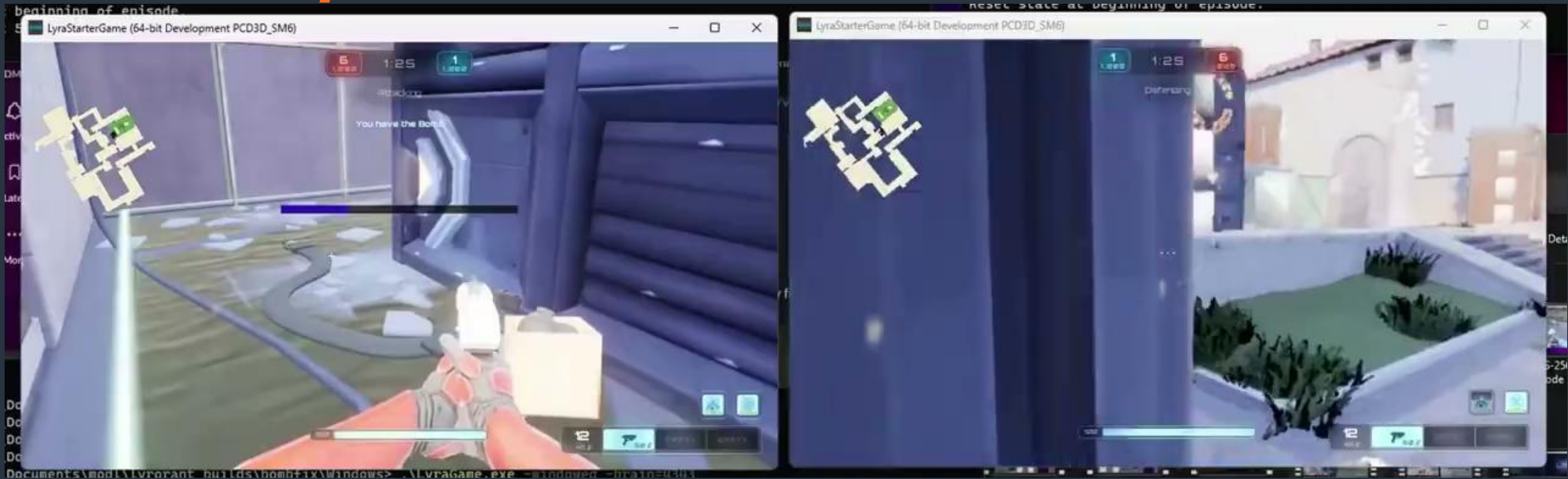
(b) Vertical rays.

Look ma, no head!



Some examples of agent behavior

Sneaky bomb defusal



Lava jumping



Waiting in smoke



Camping the smoke



Dodging an enemy



Planting the bomb and defending it



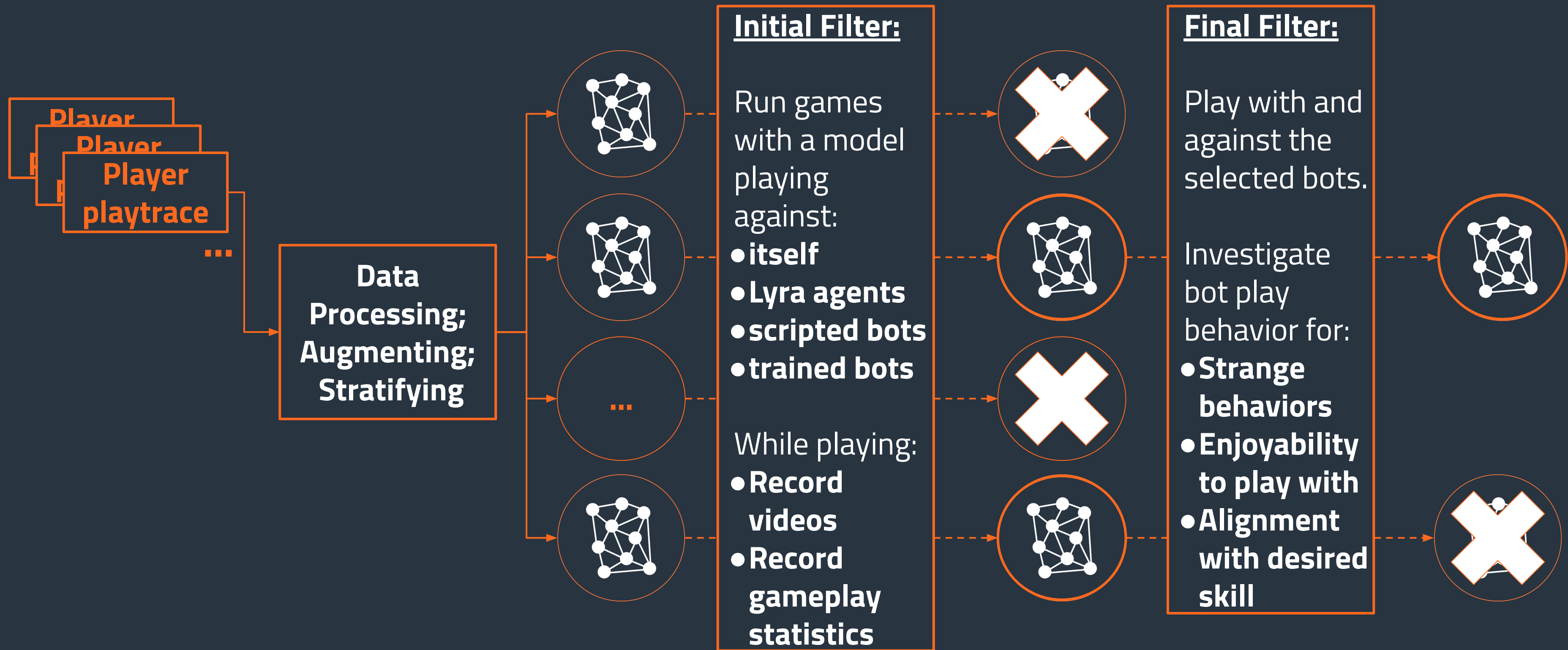
Changing an enemy and avoiding damage



Surprising an enemy



Our Evaluation Framework and Pipeline



Figuring out which model to use

ATTACK

KL

Time Duration
Speed
Shot
Shots per Kill
Kill per Round
Plant Attempt per Round
Abilities per Round

← similarity ↑

E	D	F	B	C	A
B	C	F	E	A	D
C	A	B	F	D	E
C	B	A	E	D	F
D	F	E	B	C	A
E	B	D	C	A	F
F	B	C	E	D	A

KL

Time Duration
Speed
Shot
Shots per kill
Kill per Round
Defuse Attempt per Round
Abilities per Round

← similarity ↑

D	E	B	F	C	A
B	F	D	C	E	A
C	A	B	D	E	F
C	E	D	A	B	F
B	D	E	C	F	A
E	F	C	D	A	B
F	E	C	D	B	A

Models	Similarity metric
A	1.67
B	3.87
C	4.10
D	4.33
E	3.67
F	3.43

JS

Time Duration
Speed
Shot
Shots per Kill
Kill per Round
Plant Attempt per Round
Abilities per Round

E	D	F	B	C	A
B	C	F	E	D	A
D	A	C	F	B	E
C	B	D	F	E	A
D	F	E	B	C	A
D	C	A	E	B	F
F	C	B	E	D	A

JS

Time Duration
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D	E	F	B	C	A
B	F	C	E	D	A
C	D	E	B	A	F
E	D	C	F	B	A
D	B	E	C	F	A
E	F	D	C	A	B
F	C	E	D	B	A

EMD

Time Duration
Speed
Shot
Shots per Kill
Kill per Round
Plant Attempt per Round
Abilities per Round

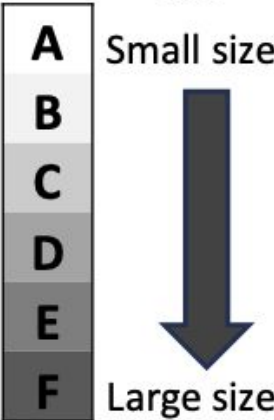
E	D	C	B	F	A
F	A	B	E	C	D
D	A	C	B	F	E
D	C	B	F	E	A
D	C	B	F	E	A
C	B	F	D	E	A
C	F	B	E	D	A

EMD

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E	D	B	C	F	A
B	E	D	F	C	A
A	C	B	D	E	F
D	B	E	C	F	A
D	B	E	C	F	A
D	E	F	A	B	C
F	E	C	D	A	B

Network size



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