



The City College  
of New York

# CSC 36000: Modern Distributed Computing *NextGen with AI Agents*

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September 8, 2025 CSC 36000

# Introduction to JAX for Distributed Computing

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# What is JAX?

JAX is a Python library for high-performance numerical computing and machine learning research.

- NumPy on Accelerators: JAX
- Composable Function Transformations: Apply transformations to your Python functions:
  - **jit**: Just-in-time compilation for speed.
  - **grad**: Automatic differentiation for optimization.
  - **vmap**: Automatic vectorization for batching.
  - **pmap**: Parallelization across multiple devices.



## Example

```
import jax import jax.numpy as jnp
# A simple Python function
def predict(params, inputs):
    return jnp.dot(inputs, params)

# Let's transform it!
grad_fn = jax.grad(predict)
fast_grad_fn = jax.jit(grad_fn)
```



## Just in time Compilation

```
from jax import jit
```

```
# A slow Python loop
```

```
def slow_function(x):
```

```
    for _ in range(5):
```

```
        x = x * 0.5 + 1.0
```

```
    return x
```

```
# A fast, compiled version
```

```
fast_function = jit(slow_function)
```

```
# The first run is slow (compilation), but subsequent runs are lightning fast!
```



## pmap

```
from jax import pmap
```

```
# Function to run on each device
```

```
def device_fn(x):
```

```
    # Each device gets a CHUNK of x
```

```
    return x * 2
```

```
# Create data and split it across devices
```

```
# Let's assume we have 8 devices
```

```
data = jnp.arange(8 * 3).reshape((8, 3)) # 8 rows, one for  
each device
```

```
# `pmap` compiles the function and runs one copy  
on each device
```

```
parallel_fn = pmap(device_fn)
```

```
# Run it! JAX handles sending each row to a  
different device.
```

```
result = parallel_fn(data)
```

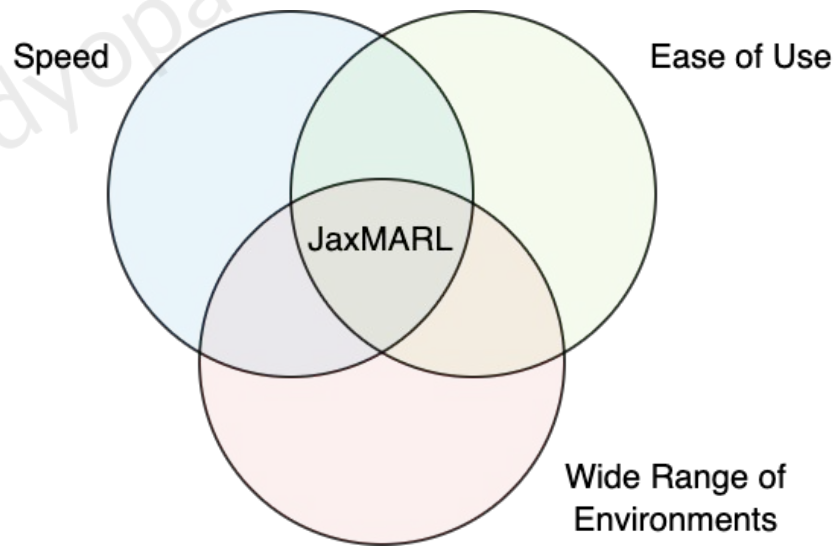
```
print(result.shape) # Output: (8, 3)
```

# Addressing Speedup with JAXMARL

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## Introduction

- Multi-Agent RL can be pretty slow!
- JAX-enabled hardware acceleration can make it 12500x faster!
- This means that experiments that once took days now take hours or minutes







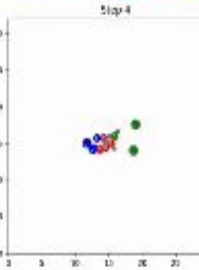
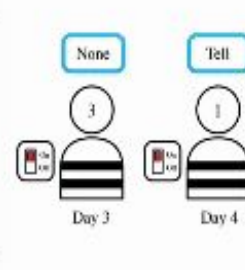
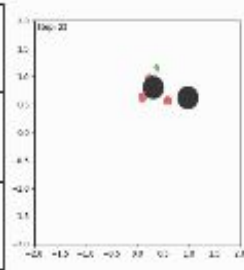
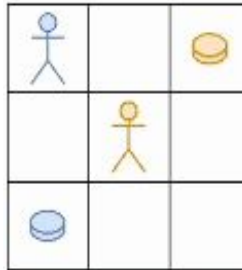
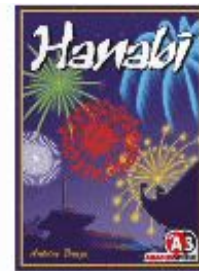
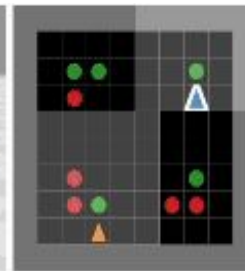
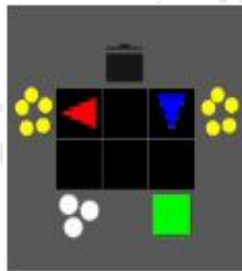
# JAXMARL

- JAX is a Python library that makes writing hardware accelerated code easy
- JAXMARL co-locates the AI agent and Multi-Agent RL environment on a GPU
- JAXMARL vectorizes environment rollouts using a single function call

# Multi-Agent Environments

- We implement 8 popular MARL environments
- We provide Q-learning and PPO baseline

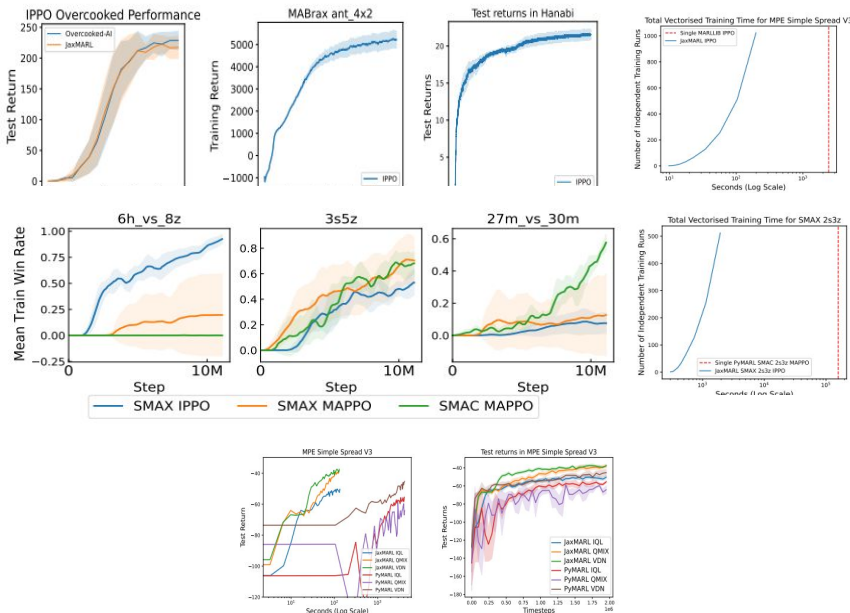
```
1 import jax
2 from jaxmarl import make
3
4 key = jax.random.PRNGKey(0)
5 key, key_reset, key_act, key_step = jax.random.split(key, 4)
6
7 # Initialise and reset the environment.
8 env = make('MPE_simple_world_comm_v3')
9 obs, state = env.reset(key_reset)
10
11 # Sample random actions.
12 key_act = jax.random.split(key_act, env.num_agents)
13 actions = {agent: env.action_space(agent).sample(key_act[i]) \
14             for i, agent in enumerate(env.agents)}
15
16 # Perform the step transition.
17 obs, state, reward, done, infos = env.step(key_step, state, actions)
```



# Baseline and Speed Results

- The Jax Environments are much much faster than CPU baselines!
- Our evaluations demonstrate that our baselines are correct and can train quickly!

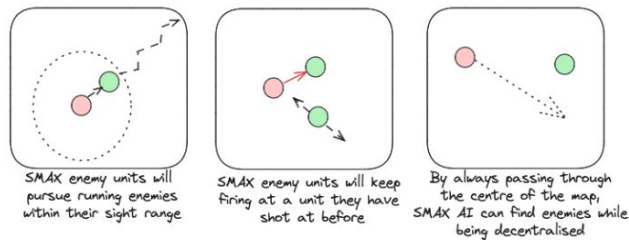
Environment	Original, 1 Env	Jax, 1 Env	Jax, 100 Envs	Jax, 10k Envs	Maximum Speedup
MPE Simple Spread	$8.34 \times 10^4$	$5.48 \times 10^3$	$5.24 \times 10^5$	$3.99 \times 10^7$	$4.78 \times 10^2$
MPE Simple Reference	$1.46 \times 10^5$	$5.24 \times 10^3$	$4.85 \times 10^5$	$3.35 \times 10^7$	$2.29 \times 10^2$
Switch Riddle	$2.69 \times 10^4$	$6.24 \times 10^3$	$7.92 \times 10^5$	$6.68 \times 10^7$	$2.48 \times 10^3$
Hanabi	$2.10 \times 10^3$	$1.36 \times 10^3$	$1.05 \times 10^5$	$5.02 \times 10^6$	$2.39 \times 10^3$
Overcooked	$1.91 \times 10^3$	$3.59 \times 10^3$	$3.04 \times 10^5$	$1.69 \times 10^7$	$8.85 \times 10^3$
MABrax Ant 4x2	$1.77 \times 10^3$	$2.70 \times 10^2$	$1.81 \times 10^4$	$7.62 \times 10^5$	$4.31 \times 10^2$
Starcraft 2s3z	$8.31 \times 10^1$	$5.37 \times 10^2$	$4.53 \times 10^4$	$2.71 \times 10^6$	$3.26 \times 10^4$
Starcraft 27m vs 30m	$2.73 \times 10^1$	$1.45 \times 10^2$	$1.12 \times 10^4$	$1.90 \times 10^5$	$6.96 \times 10^3$
STORM	—	$2.48 \times 10^3$	$1.75 \times 10^5$	$1.46 \times 10^7$	—
Coin Game	$1.97 \times 10^4$	$4.67 \times 10^3$	$4.06 \times 10^5$	$4.03 \times 10^7$	$2.05 \times 10^3$



# Star-Craft with SMAX

- We improve on SMAC and SMACv2's heuristics in SMAX
- The enemy heuristic is now fully decentralised meaning win-rates below 50% represent a concrete failure to learn
- SMAX is also faster and in pure Python so more customisable!

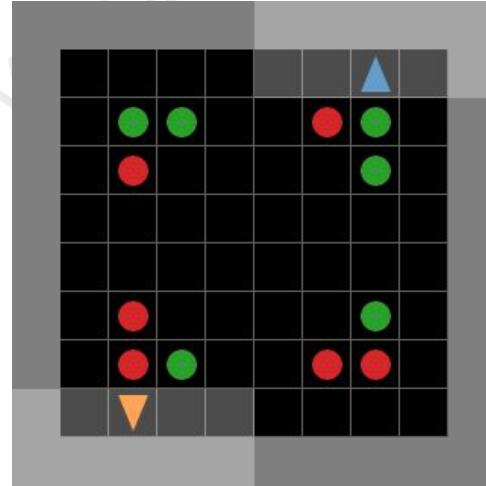
SMAX Heuristic AI



Scenario	Ally Units	Enemy Units	Start Positions
2s3z	2 stalkers and 3 zealots	2 stalkers and 3 zealots	Fixed
3s5z	3 stalkers and 5 zealots	3 stalkers and 5 zealots	Fixed
5m_vs_6m	5 marines	6 marines	Fixed
10m_vs_11m	10 marines	11 marines	Fixed
27m_vs_30m	27 marines	30 marines	Fixed
3s5z_vs_3s6z	3 stalkers and 5 zealots	3 stalkers and 6 zealots	Fixed
3s_vs_5z	3 stalkers	5 zealots	Fixed
6h_vs_8z	6 hydralisks	8 zealots	Fixed
smacv2_5_units	5 uniformly randomly chosen	5 uniformly randomly chosen	SMACv2-style
smacv2_10_units	10 uniformly randomly chosen	10 uniformly randomly chosen	SMACv2-style
smacv2_20_units	20 uniformly randomly chosen	20 uniformly randomly chosen	SMACv2-style

# STORM

- STORM: Spatial-Temporal Representations of Matrix Games
- STORM allows to represent matrix games as grid-world scenarios
- Presents new challenges such as partial observability, multi-step agent interactions and longer time horizons



# Questions?

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