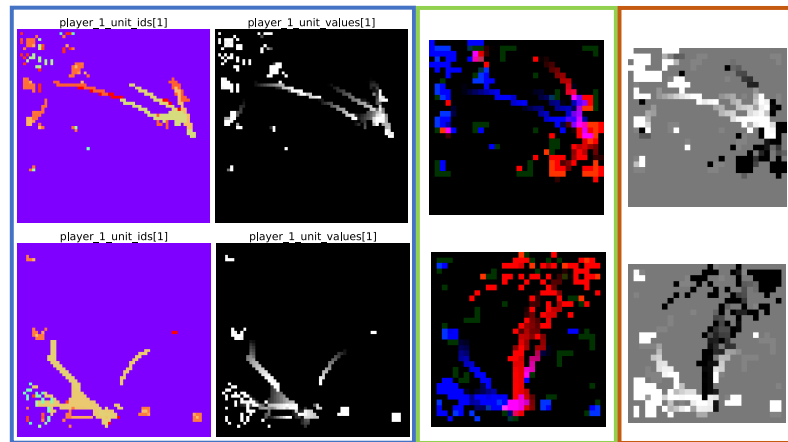


StarCraftImage:

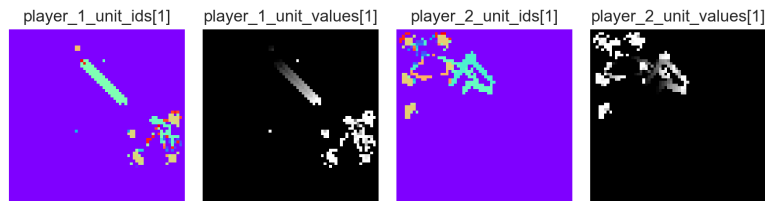
A Dataset For Prototyping Spatial Reasoning
Methods for Multi-Agent Environments



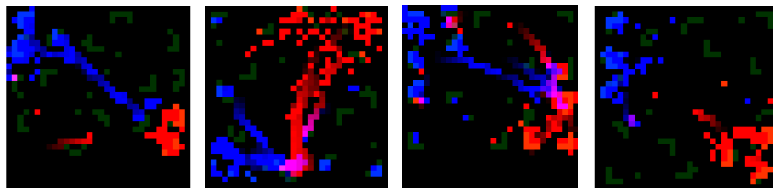
Sean Kulinski, Nicholas R. Waytowich, James Z. Hare, David I. Inouye

StarCraftImage is an easy-to-use image dataset with intelligent (and adversarial) multi-agent behavior

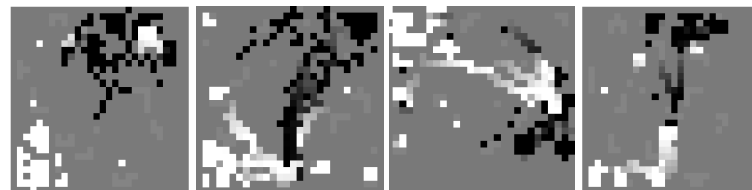
- StarCraft II game states were extracted from 60K publicly available match recordings
- StarCraftImage contains 3.6M images that summarize unit locations in a 10 second window
- The dataset contains intelligent (and adversarial) multi-agent behavior along with rich metadata
- **StarCraftCIFAR10** and **StarCraftMNIST** exactly match CIFAR10 and MNIST formats (only URL change from PyTorch MNIST/CIFAR10 datasets)



A [StarCraftHyper](#) hyperspectral Image (Flattened To RGB Image)



Four 32x32 RGB Images from [StarCraftCIFAR10](#)

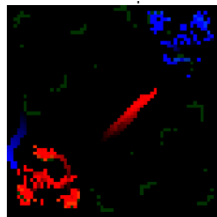


Four 28x28 Grayscale Images from [StarCraftMNIST](#)

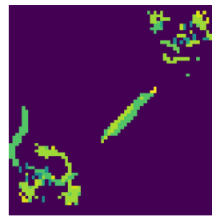
StarCraftImage is applicable to many spatial reasoning tasks

- **Unit Identification** - Given a RGB image, predict unit ID information (image colorization)
- **Multi-Object Tracking** - Predict unit movement in the next 10 seconds (next window prediction)
- **Global Reasoning** - Predict which player will win (classification)
- **Missing Data Imputation** - Apply noise simulation (e.g., a sensor network) and predict de-noised image

Input RGB Image

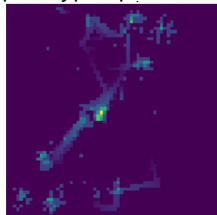


Ground Truth Colorization

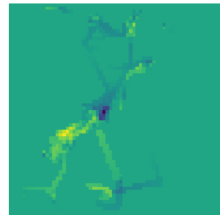


Unit Identification: [StarCraftCIFAR10](#) → [StarCraftHyper](#)

Input Hyperspectral Image

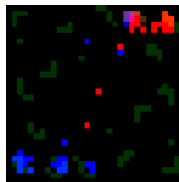


Ground Truth Next Window



Next Window Prediction: [StarCraftHyper](#) → [StarCraftHyper](#)

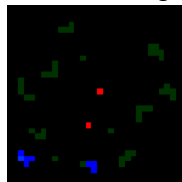
Input Image



Sensor Visual Field



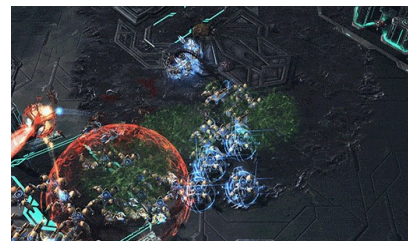
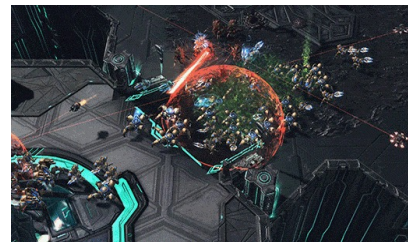
Masked Image



Applying a simulated sensor network to StarCraftImage

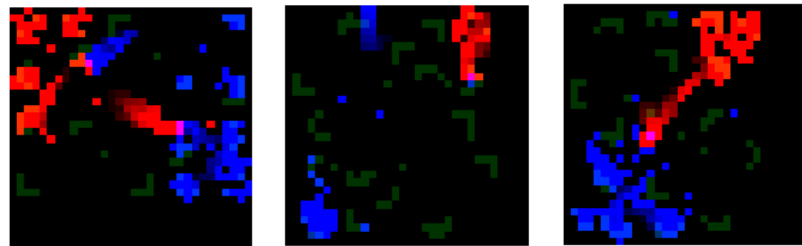
Game replays are rich data sources for ML but require significant overhead to use

- StarCraft II (SCII) is a real-time strategy game
 - Replay packs with thousands of human-played SCII matches provide intelligent (and adversarial) multi-agent behaviors
 - The PySC2 API enables direct access to the entire game state
- However, extracting ML-ready representations of games requires many hours of engineering work
- Our goal: Create a multi-agent spatial reasoning dataset that is as easy to use as MNIST and CIFAR10

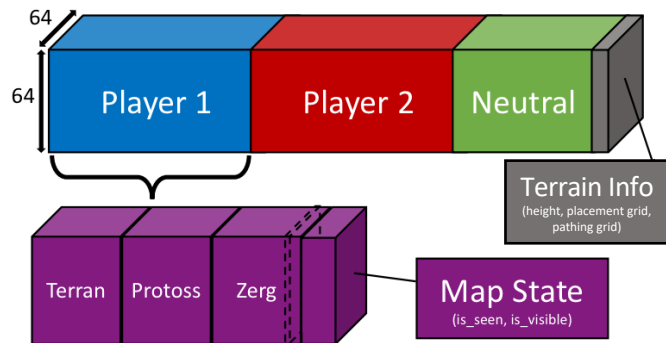


Extracting StarCraftImage

- We use PySC2 to replay an SCII match and extract all unit information at each frame
- We summarize 10 second windows into a single image
- Hyperspectral images (**StarCraftHyper**) consist of 384 channels each representing a different unit type (e.g., channel 51 is Player 1's Terran Battlecruiser units)
- Values at each channel show when the last time a unit was seen during the 10 second window (this produces a ghosting effect)
- Map state information such as visibility and creep (Zerg-specific) are included



Three images, each summarizing 10 seconds of a StarCraft II match



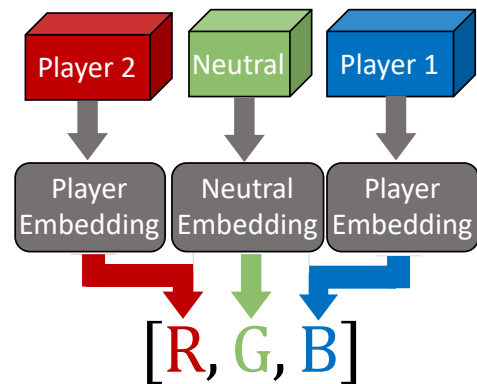
153	155	0	0	0	240	0	0
0	157	0	0	0	241	242	0
0	158	159	0	0	0	244	245
0	0	160	0	0	0	0	0
0	0	162	163	0	0	0	0
0	0	0	165	169	170	0	0
0	0	0	0	0	173	0	0
0	0	0	0	0	175	0	0

Value
Matrix:

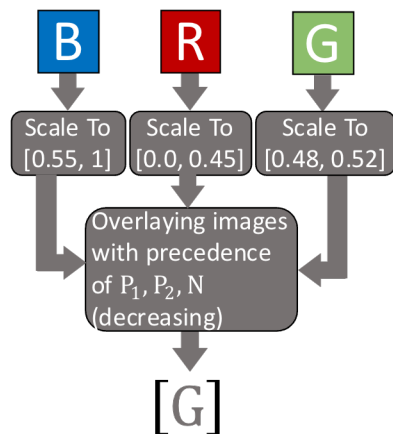
Values are "last seen" time
stamp in window [0, 255]
where 0 := not seen

Simplifying to StarCraftMNIST and StarCraftCIFAR10

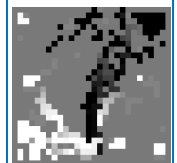
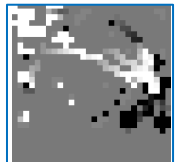
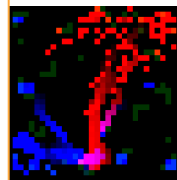
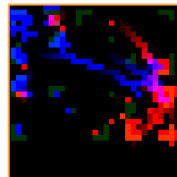
- As a simpler alternative, we further processed **StarCraftHyper** to exactly fit the formats of CIFAR10 and MNIST (only URL change required)
- StarCraftCIFAR10**– Compressed player unit information into a 3 channels
- StarCraftMNIST**– Compressed further to 28x28 grayscale image
- The 10 labels are map name (5 maps) + first or second half of match (e.g., Class 1 = (“Odyssey”, "First half"), Class 2 = (“Odyssey”, "Second half"), ...)



StarCraftHyper → StarCraftCIFAR10

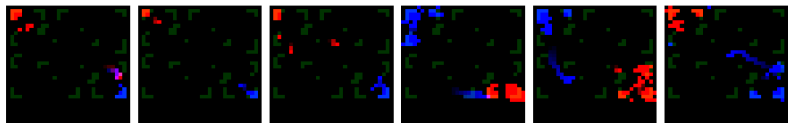


StarCraftCIFAR10 → StarCraftMNIST

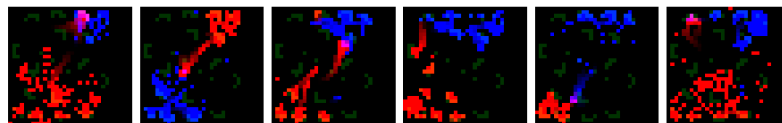


10-Class Examples from StarCraftImage

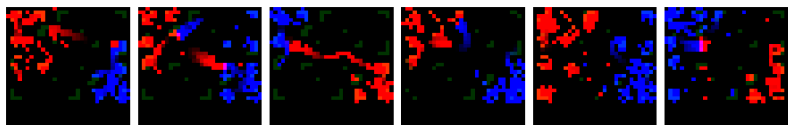
Images from class 0



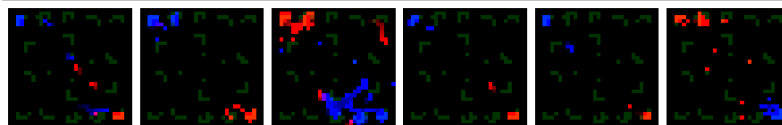
Images from class 5



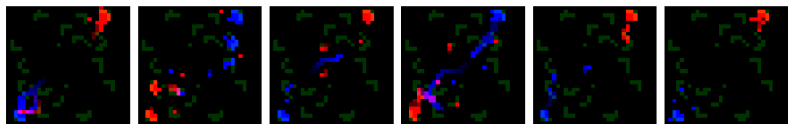
Images from class 1



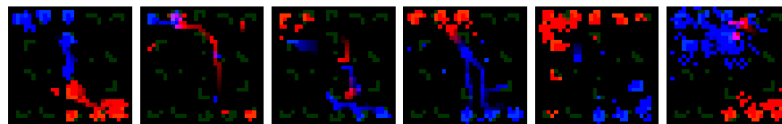
Images from class 6



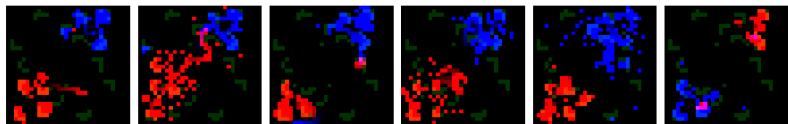
Images from class 2



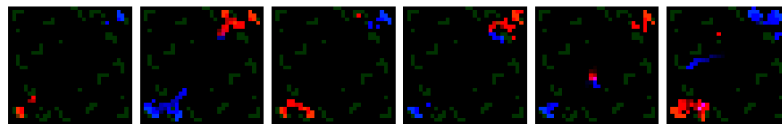
Images from class 7



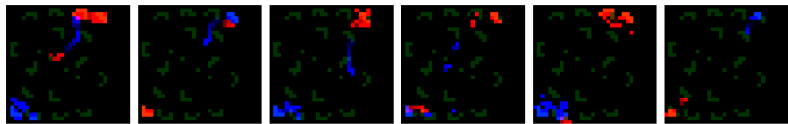
Images from class 3



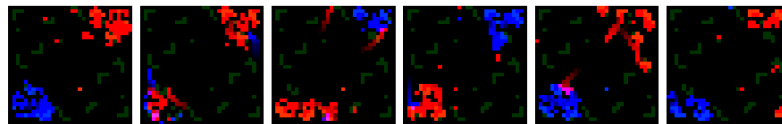
Images from class 8



Images from class 4



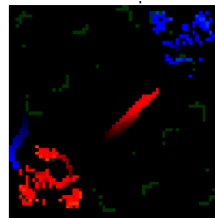
Images from class 9



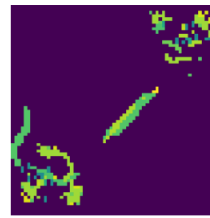
StarCraftImage is applicable to many spatial reasoning tasks

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- **Missing Data Imputation** - Apply noise simulation (e.g., a sensor network) and predict de-noised image

Input RGB Image

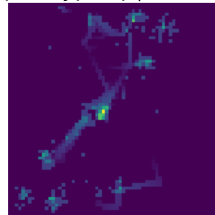


Ground Truth Colorization

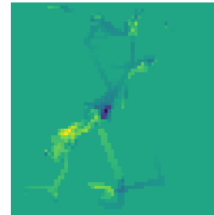


Unit Identification: [StarCraftCIFAR10](#) → [StarCraftHyper](#)

Input Hyperspectral Image

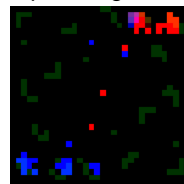


Ground Truth Next Window



Next Window Prediction: [StarCraftHyper](#) → [StarCraftHyper](#)

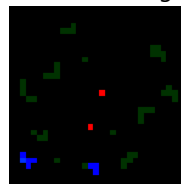
Input Image



Sensor Visual Field



Masked Image



Applying a simulated sensor network to StarCraftImage

Collected sample metadata allows for easy filtering and splitting for task modification

- All samples are paired with game metadata: `player_resource_counts`, `map_name`, `player_unit_races`, `player_ranking`, etc.
- Metadata can be used to split samples for task modifiers, such as domain generalization: training on $6/7$ maps and testing on remainder
- We found model performance on StarCraftImage tracks with real-world spatial reasoning experiment (the model ranking order is similar):

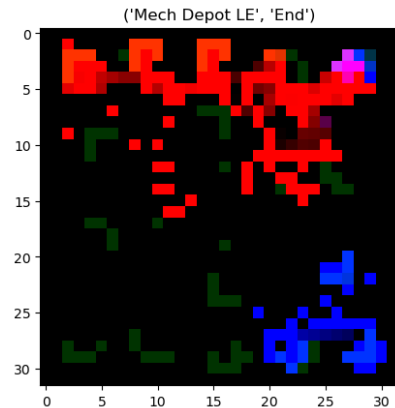
	Segformer	Lawin	Resnet-18	Resnet-34	Resnet-50
StarCraft-Image	17.9%	27.0%	56.6%	58.5%	62.5%
DOTA-Satellite	35.0%	34.1%	52.4%	52.8%	53.6%

StarCraftImage is ready to use in two lines of code

```
[1]: from sc2image.dataset import StarCraftCIFAR10
```

```
[2]: sc_cifar = StarCraftCIFAR10(root='./data', train=True)
```

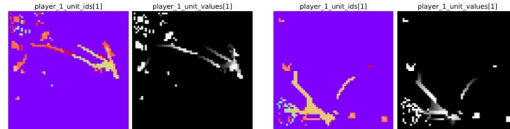
```
[3]: import matplotlib.pyplot as plt  
x, class_idx = sc_cifar[0]  
plt.imshow(x)  
plt.title(sc_cifar.classes[class_idx]);
```



StarCraftImage Conclusion

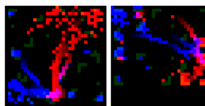
StarCraftHyper:

- 3.6+ million image samples
- Summarizes 10 seconds of human SCII match
- Hyperspectral images with full unit information



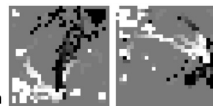
StarCraftCIFAR10:

- 60,000 32x32px RGB images
- Exactly matches the CIFAR10 format
- Difficult 10-class classification problem



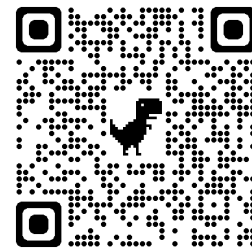
StarCraftMNIST:

- 70,000 28x28px grayscale images
- Exactly matches the MNIST format
- Difficult 10-class classification problem



- Video games can serve as pseudo-realistic simulations of complex human-agent actions, but require many hours of engineering to setup for ML
- StarCraftImage is an **easy-to-use**, yet complex behaved image-based dataset for **prototyping spatial reasoning** algorithms
- StarCraftImage has many applications (**Unit Identification**, **Multi-Object Tracking**, etc.) and possible extensions (**Simulated Partial Observations**)
- What applications will you use StarCraftImage for?
We'd love to hear your ideas!

Q & A



StarCraftImage

A Dataset For Prototyping Spatial Reasoning Methods for Multi-Agent Environments

Sean Kulinski, Nicholas R. Waytowich, James Z. Hare, David I. Inouye

To find more information: <https://starcraftdata.davidinouye.com/>