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Combining Algorithms for More General AI

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Introduction

2 decades since the first convolutional neural network [1] was introduced the AI sub-domains of classification, regression and prediction still rely heavily on a few ML architectures despite their flaws of being hungry for data, time, and high-end hardware while still lacking generality [2]. In order to achieve more general intelligence it is necessary to look for new ML system frameworks that will build on past success while also moving forward.

Objective

In this work two neural inspired algorithms are combined. A convolutional neural network (CNN) which performs well on image recognition tasks and Numenta's spatial pooler(SP)[3] which is an unsupervised algorithm meant to capture statistical information in the same way as the neocortex. The goal is to demonstrate that similar image inputs to the system create similar yet distinct outputs at the highest SP layer. If successful, this algorithmic combination may warrant further investigation and use.

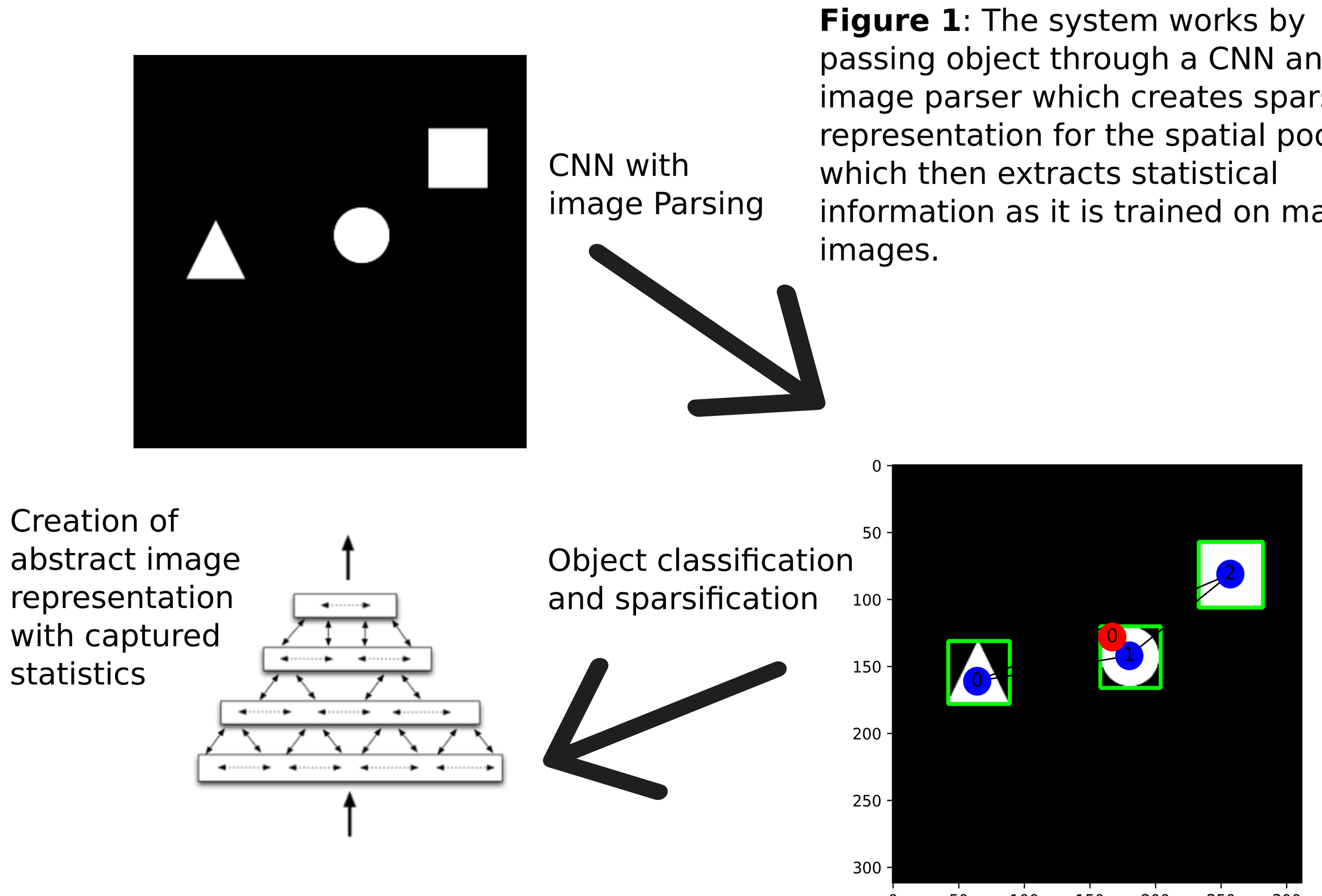
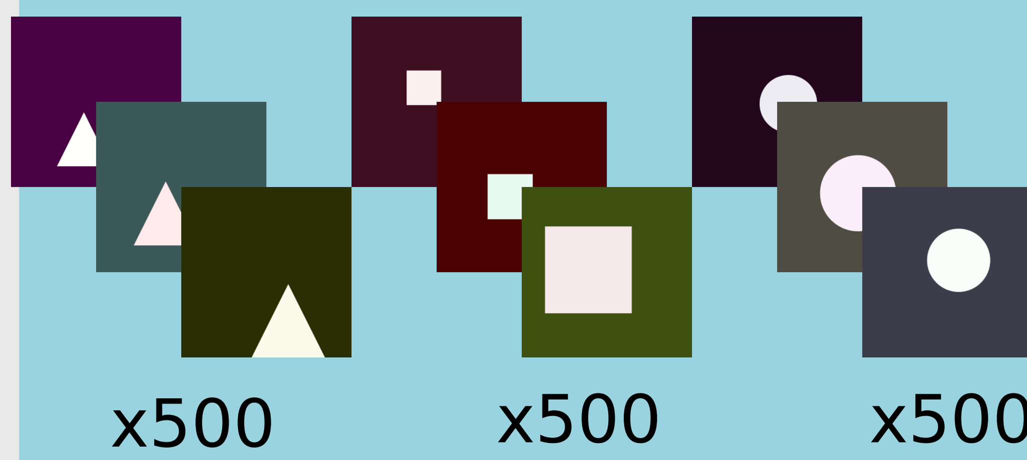


Figure 1: The system works by passing object through a CNN and image parser which creates sparse representation for the spatial pooler which then extracts statistical information as it is trained on many images.

Methodology



CNN Training Set

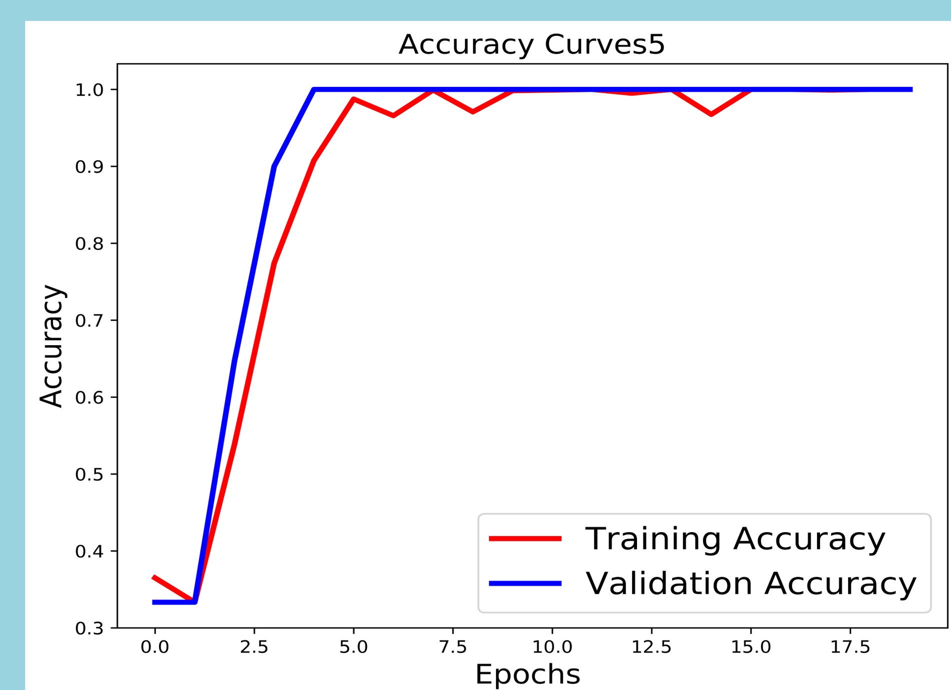


Figure 2: Convolutional neural works are superb at image recognition and the purpose of this neural network was to find the simple objects within the image for later processing.

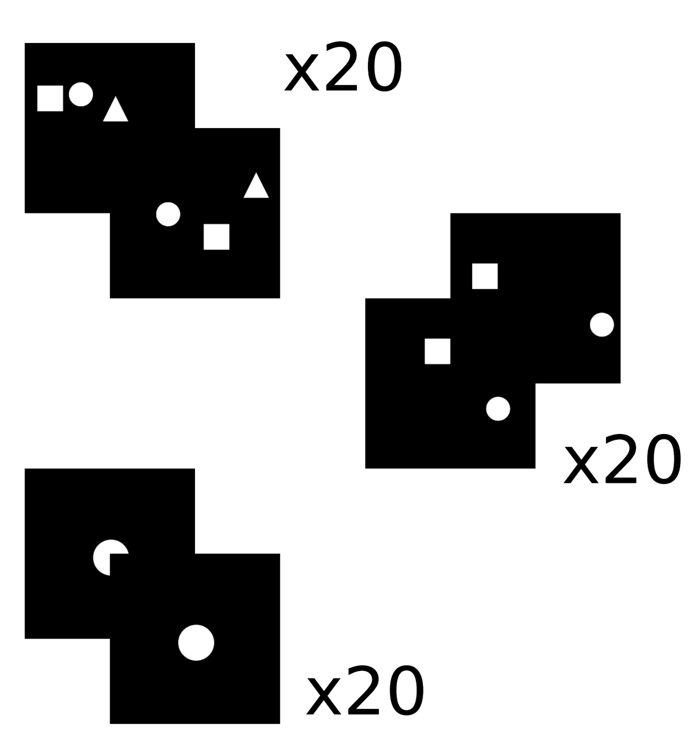
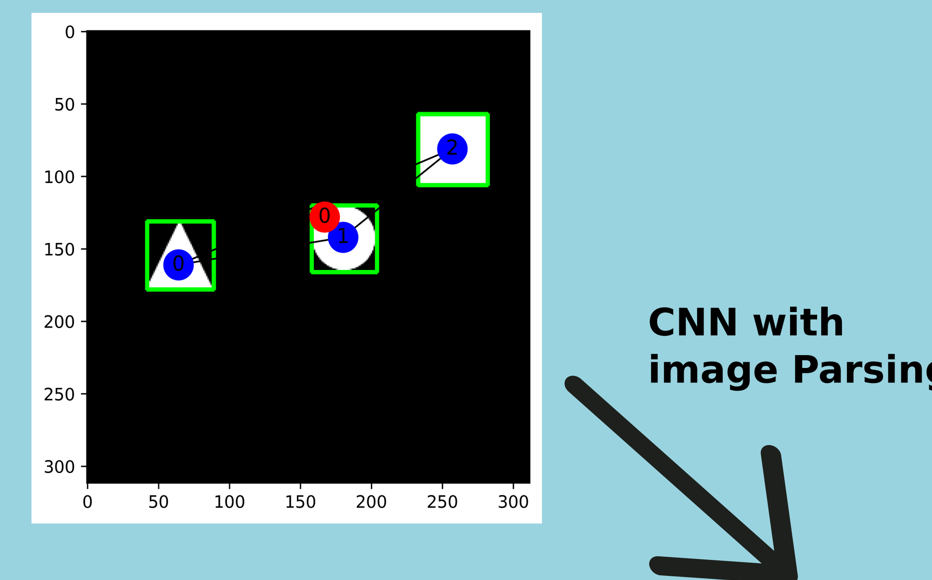


Figure 3: Three sets of 20 structurally similar images with slight variations of object placement and object area were fed to the network in order to teach the SP the statistical similarities across the images.



CNN with image Parsing

```
('Area of the object:', 1123.5)
('Area of the object:', 1580.0)
('Area of the object:', 2297.0)
['Object 0 is a', 'Circle']
['Object 1 is a', 'Square']
['Object 2 is a', 'Square']
('Distance from center 0 to 1: ', 117.5457357797381)
('Distance from center 1 to 2: ', 98.2344135219425)
('Distance from center 0 to 2: ', 208.92343095019285)
```

For each object the image parsing algorithm[4] and the CNN extract object type, distance to each neighbor, and area which is then fed into the spatial pooler as a sparse distributed representation (SDR). SDRs are a good balance between dense encoding and localised encoding and are observed in the primate brain[5].

SDR processed via 3 spatial pooler layers

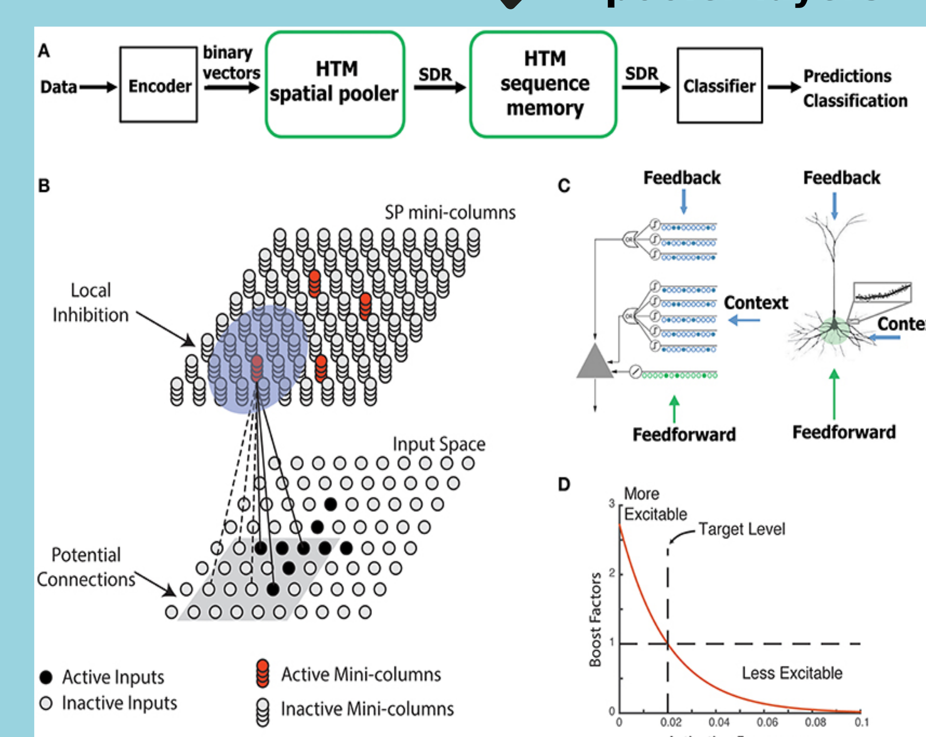


Figure 4: The spatial pooler[3] is an unsupervised learning algorithm using Hebbian learning rules and homeostatic excitability control to find statistical invariance in its input space. One SP layer works to simulate synaptic connections between cortical layers in the brain and multiple layers find higher order patterns.

Results

The system was fed 3 sets of 20 images of similar structure but decreasing complexity (figure 3). The system showed no overlap of the output neuron across the third layer for all three input types. This shows that the system made distinct representations of the three input types but did not recognize the statistical similarities. More source information must be added to the sytem to improve this.

```
Layer 3 TriangleSquareCircle Out:
[ 56  57  60 131 132 133 135 136 139 140]
[ 50  52  55  59  65 128 134 137 141 145]
Layer 3 CircleSquare Out:
[ 3   4   5   6   8   9  10  31  79  81]
[14  18  28  30  33  37  38  42  75  78]
Layer 3 Circle Out:
[14  15  16  17  18  20  21  22  23  26]
[ 8   9  10  11  12  13  19  24  25  27]
```

Figure 5: The output of layer 3 for the images shown above. Each line represents one image. The images are those in figure 3.

References, Acknowledgements, Contact Information

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