Interpretation of the Spatial Pooler SDR Reconstruction

Information Technology Course Module Software Engineering by Damir Dobric / Andreas Pech

ML 23/24-04 Implement the Spatial Pooler SDR Reconstruction

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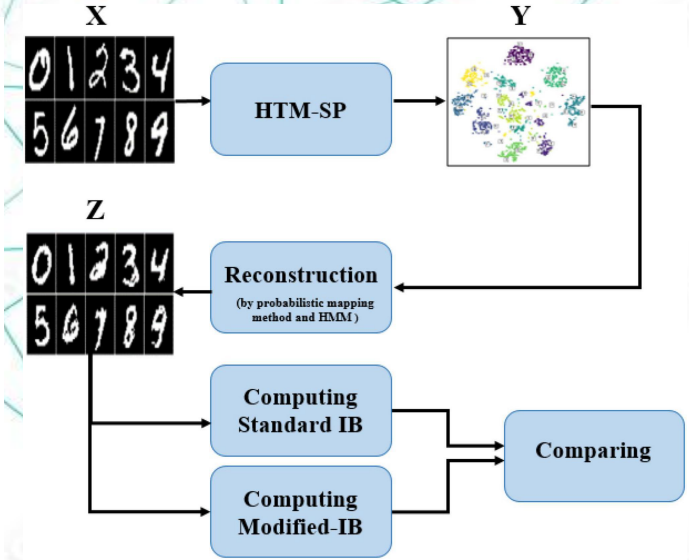
Problem Statement

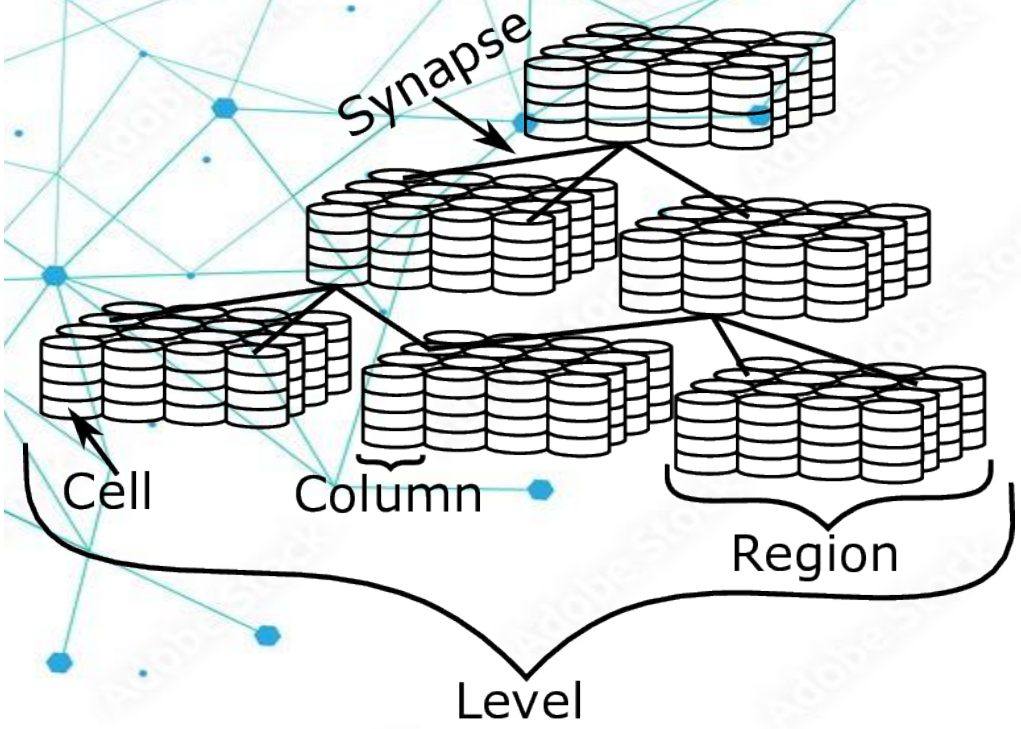
ML 23/24-04 Implement the Spatial Pooler SDR Reconstruction

Design an experiment to investigate and visualize the reconstruction process performed by the Reconstruct() method in the NeocortexAPI's SpatialPooler class.



Introduction

1. **Hierarchical Temporal Memory (HTM) is a fascinating machine learning technique inspired by the neocortex. It's designed to learn and predict sequences, aiming to generate generalized representations for similar inputs.**
2. **Sparse Distributed Representations (SDRs): These are fundamental in Hierarchical Temporal Memory (HTM) systems. The HTM spatial pooler (SP).**



Methods

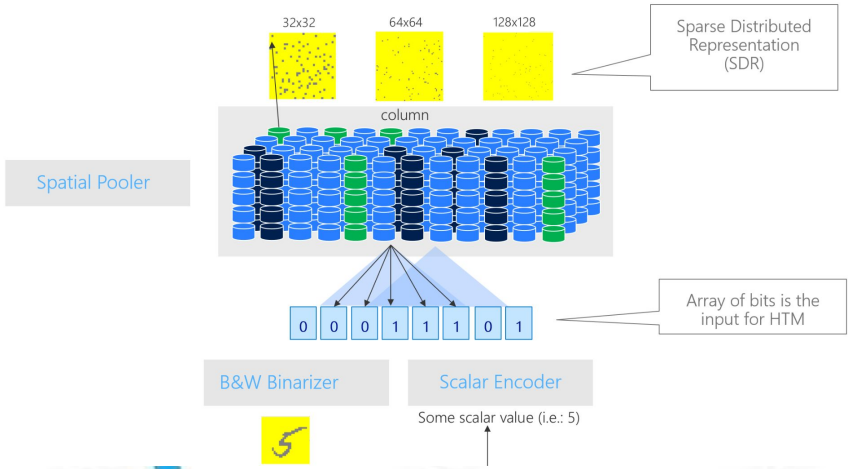
A. Encoder

a. Scalar encoder

The Scalar Encoder plays a crucial role in the Spatial Pooler (SP), drawing inspiration from the neocortex. Its main purpose is to transform scalar input values into Sparse Distributed Representations (SDRs). To achieve this, the Scalar Encoder follows specific rules, including competitive Hebbian learning and homeostatic excitability control.

b. Image Binarizer

The Image Binarizer is a preprocessing step used to convert continuous-valued pixel intensities in an image into binary values (usually 0 or 1). It simplifies the image representation by thresholding the pixel values.



B. Spatial Pooler

The Spatial Pooler converts input patterns into Sparse Distributed Representations (SDRs) in an ongoing, online manner. The HTM temporal memory learns temporal sequences from these SDRs and generates predictions for future inputs. The spatial pooler organizes data in the spatial dimension by creating pools or clusters. During the spatial pooler's learning process, each input pattern is compared to a database of other patterns.

C. Sparse Distributed Representations

Sparse distributed representations (SDRs) are a type of data encoding method used in various fields, including neuroscience, artificial intelligence, and machine learning. In SDRs, information is represented by activating a small percentage of elements in a large vector or array, while the rest remain inactive or "sparse."

D. Reconstruction

Its is a method within the spatial pooler class. When this method is invoked, it produces a dictionary where the input indices serve as keys, and their corresponding aggregated permanence values act as values. Essentially, this dictionary represents the reconstructed input pattern based on the active columns in the spatial pooler.

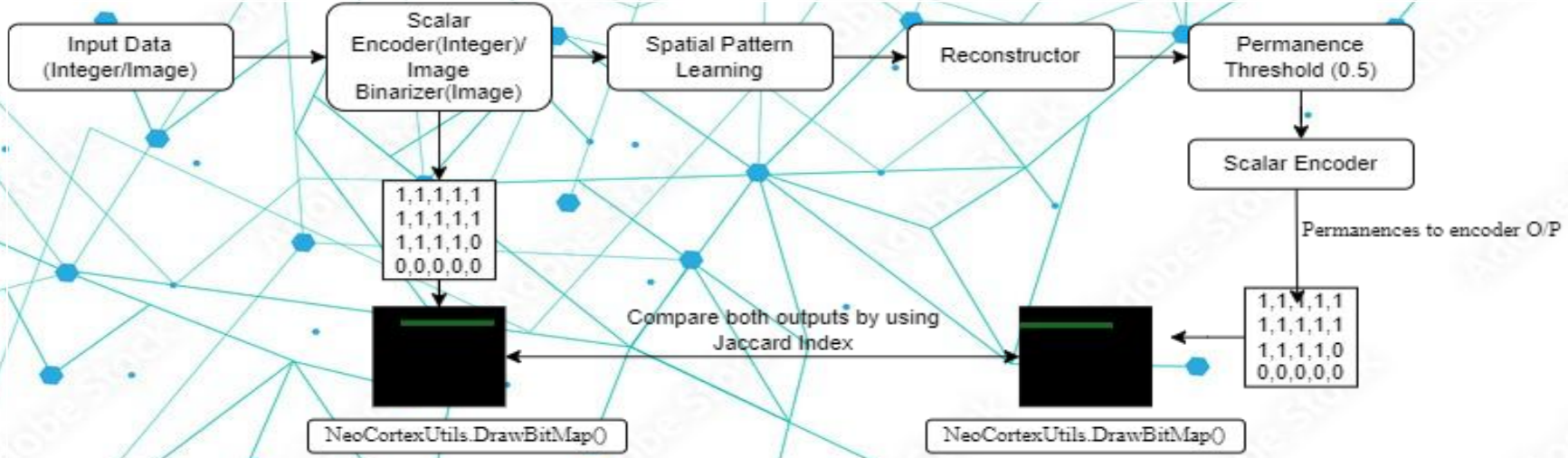
```
2 references
public Dictionary<int, double> Reconstruct(int[] activeMiniColumns)
{
    if (activeMiniColumns is null)
    {
        throw new ArgumentNullException(nameof(activeMiniColumns));
    }

    var columns = connections.GetColumnList(activeMiniColumns);
    Dictionary<int, double> permanences = new Dictionary<int, double>();

    // Iterate through all columns and collect all synapses.
    foreach (var column in columns)
    {
        column.ProximalDendrite.Synapses.ForEach(s =>
        {
            double currPerm = 0.0;

            // Check if the key already exists
            if (permanences.TryGetValue(s.InputIndex, out currPerm))
            {
                // Key exists, update the value
                permanences[s.InputIndex] = s.Permanence + currPerm;
            }
            else
            {
                // Key doesn't exist, add a new key-value pair
                permanences[s.InputIndex] = s.Permanence;
            }
        });
    }
```

Experiment


Input Data (Integer/Image)
Scalar Encoder(Integer)/ Image Binarizer(Image)
Spatial Pattern Learning
Reconstructor
Permanence Threshold (0.5)
Scalar Encoder
Permanences to encoder O/P
1,1,1,1,1 1,1,1,1,1 1,1,1,1,0 0,0,0,0,0
1,1,1,1,1 1,1,1,1,1 1,1,1,1,0 0,0,0,0,0
Compare both outputs by using Jaccard Index
NeoCortexUtils.DrawBitMap()
NeoCortexUtils.DrawBitMap()

User Interface (UI)

A simple user interface using switch case to implement both parts of the experiment together.

```
Welcome to our project ML 23/24-04
Implement the Spatial Pooler SDR Reconstruction
Created by:
    Subham Singh[1506413]
    Amit Maity[1502808]
    Ruby Kiran[1504617]


Press 1 to run the experiment with Scalar values using Scalar Encoder
Press 2 to run the experiment with a Mnist Image using Image Binarizer
Press any other key to exit
```

Results

Case 1 : SDR reconstruction for Scalar Values:

The analysis resulted in computing Sparse Distributed Representations (SDRs) for random integer values (100 to 1000), followed by input reconstruction from the SDRs. Comparison of input and reconstructed bitmaps using BitmapComparator revealed visual similarity. Further analysis involved calculating the Jaccard index and bitmap similarity percentage for additional insights.

```
Input: 3, Bitmap Similarity Percentage: 95.15865148104531
Input: 3, Jaccard Index Percentage =  57.89473684210527
Input SDR: 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
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, 0, 0, 0
Reconstructed SDR: 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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 0, 0, 0, 0, 0, 0
Input: 4, Bitmap Similarity Percentage: 95.15865148104531
Input: 4, Jaccard Index Percentage =  57.89473684210527
Input SDR: 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
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, 0, 0, 0
Reconstructed SDR: 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
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 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
 0, 0, 0, 0, 0, 0
```
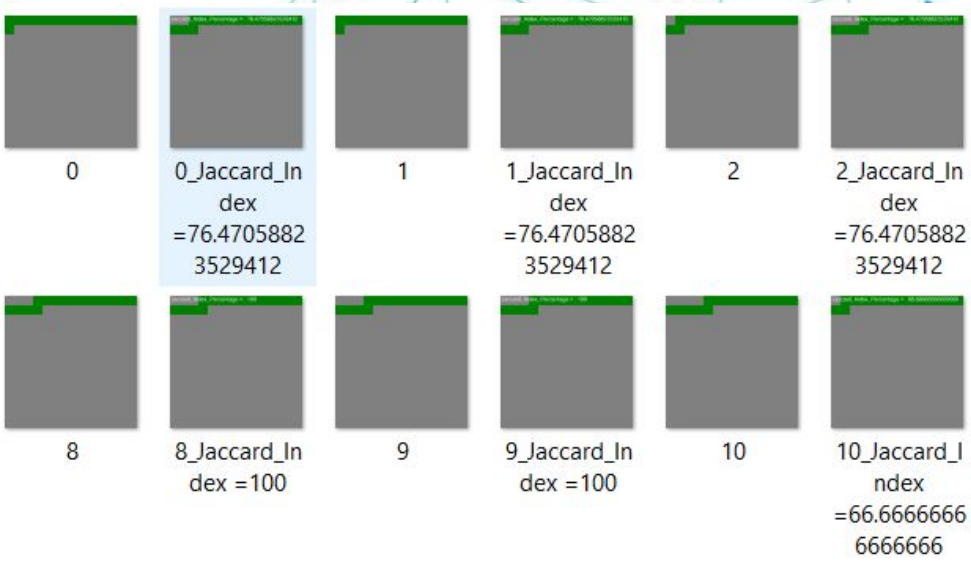

Results



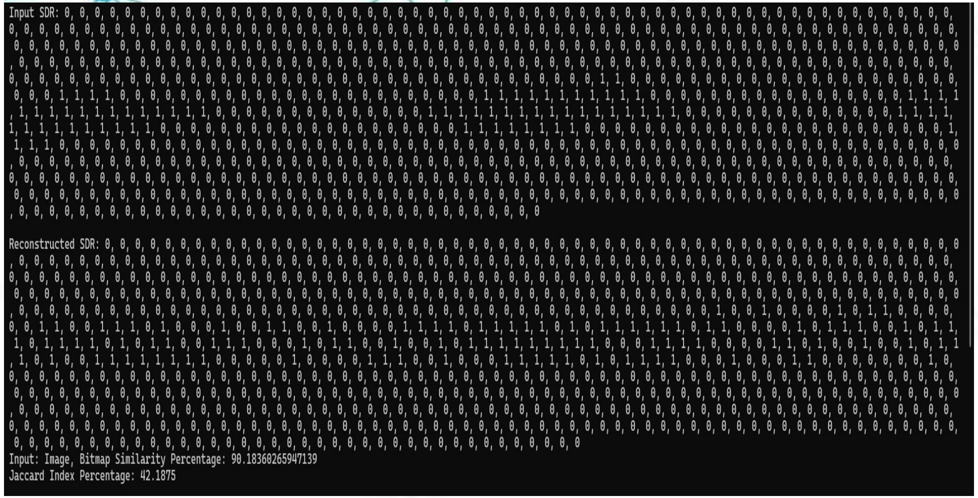
Case -1 :

Upon creating bitmaps for the input SDR and the Reconstructed SDR, it was observed that we were able to achieve a similarity of 100 percent with average similarity of 82% based on the image shown.

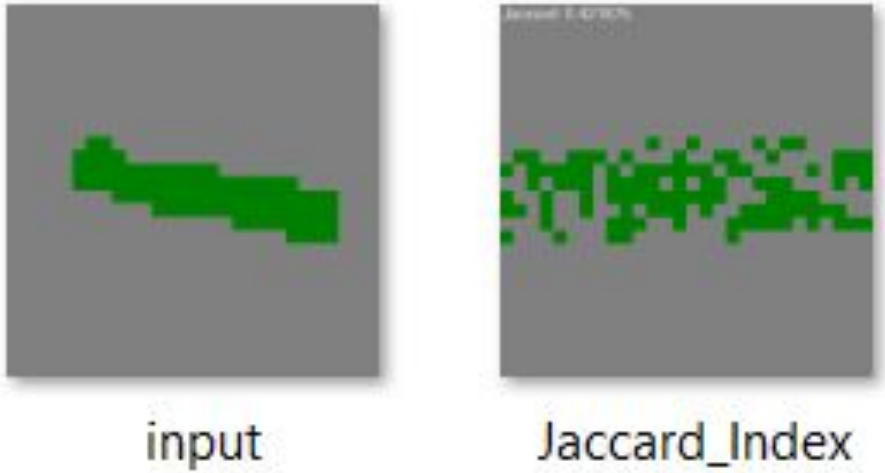
Results

Case 2 : SDR reconstruction for a single image:

MNIST dataset subset (digit 1) underwent learning in SP, yielding SDRs. Upon reconstruction, the original and reconstructed SDRs are compared using Jaccard Index



Results



Case -2 :

Upon creating bitmaps for the input SDR and the Reconstructed SDR, it was observed that we were able to achieve a similarity (Jaccard Index Percentage) of 42% (approx).

Future Scope

1. Batch image processing can be implemented.
2. Improving the accuracy of the reconstructed images.
3. The SP can be trained using images of different dimensions, color gradients and filters for a robust training.
4. The UI can be improved with the goal of providing a more user friendly experience while performing the experiment.


THANK YOU!