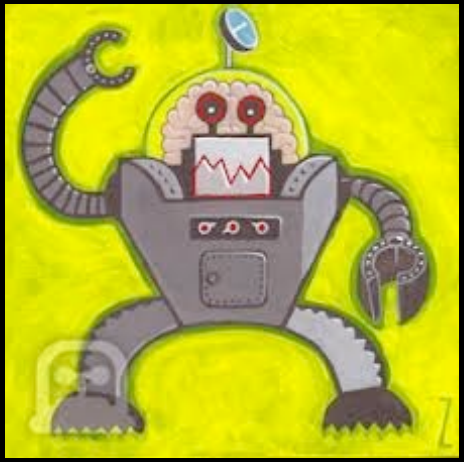


Neocognitron

Fukushima, K. and Miyake, S. 1981

presented by Sam Thomson
Oct. 3, 2013

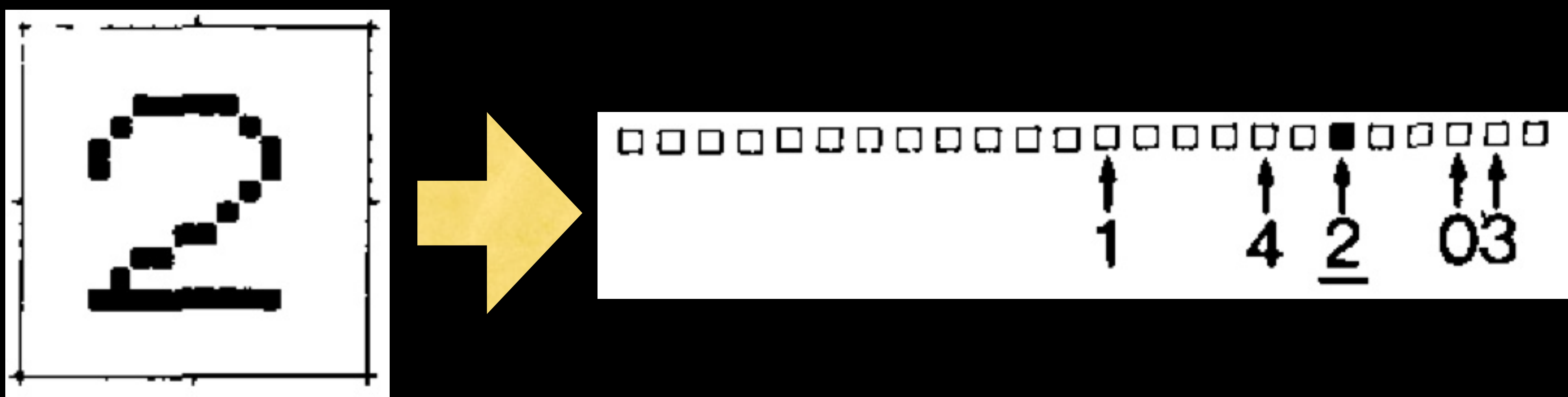
Overview

- multilayer neural network inspired by the mammalian visual system
- unsupervised image classification, tolerant to shifts and deformations
- improvement on the cognitron

Kunihiko Fukushima

Task

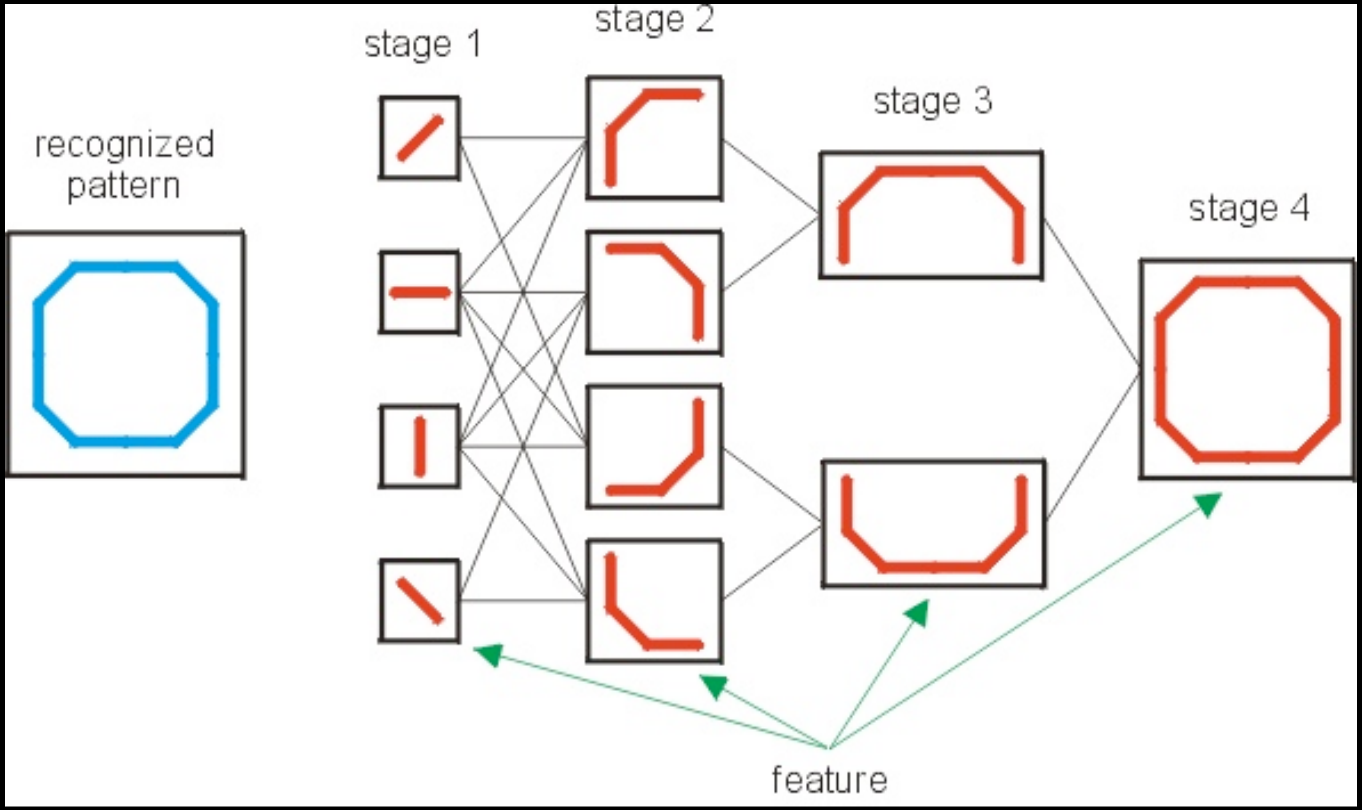
- Unsupervised handwritten character recognition
  - input - unlabeled images
  - output - vector, with each bit hopefully encoding a distinct class of images



Design

Design - High Level

- multiple (usually about 3 hidden) *layers*
- Successive layers recognize higher-level patterns

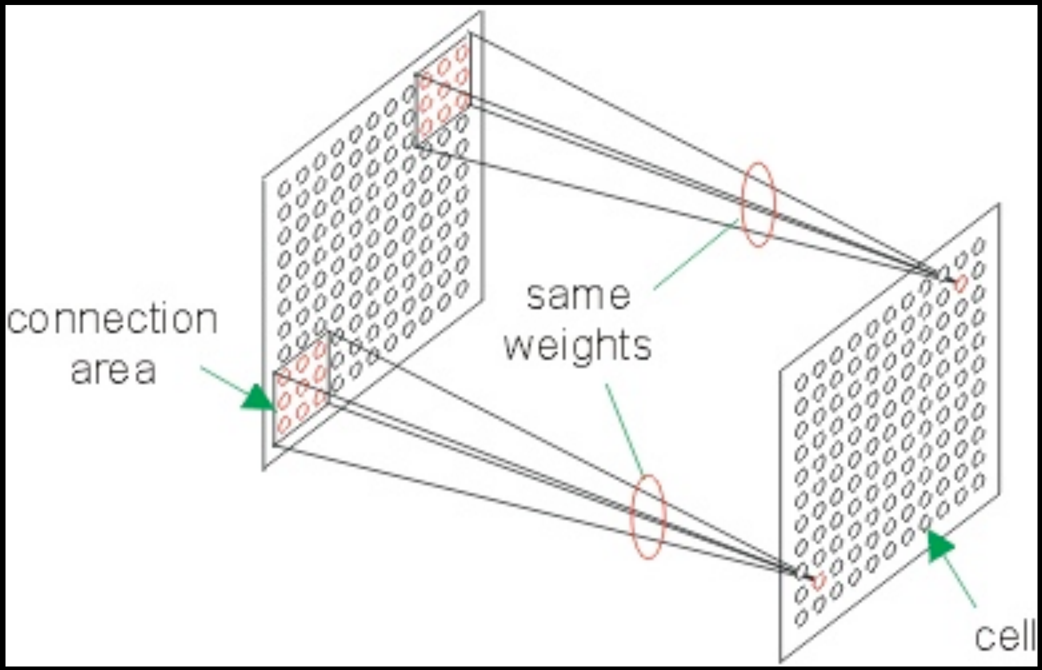


Design - Makeup of a Layer

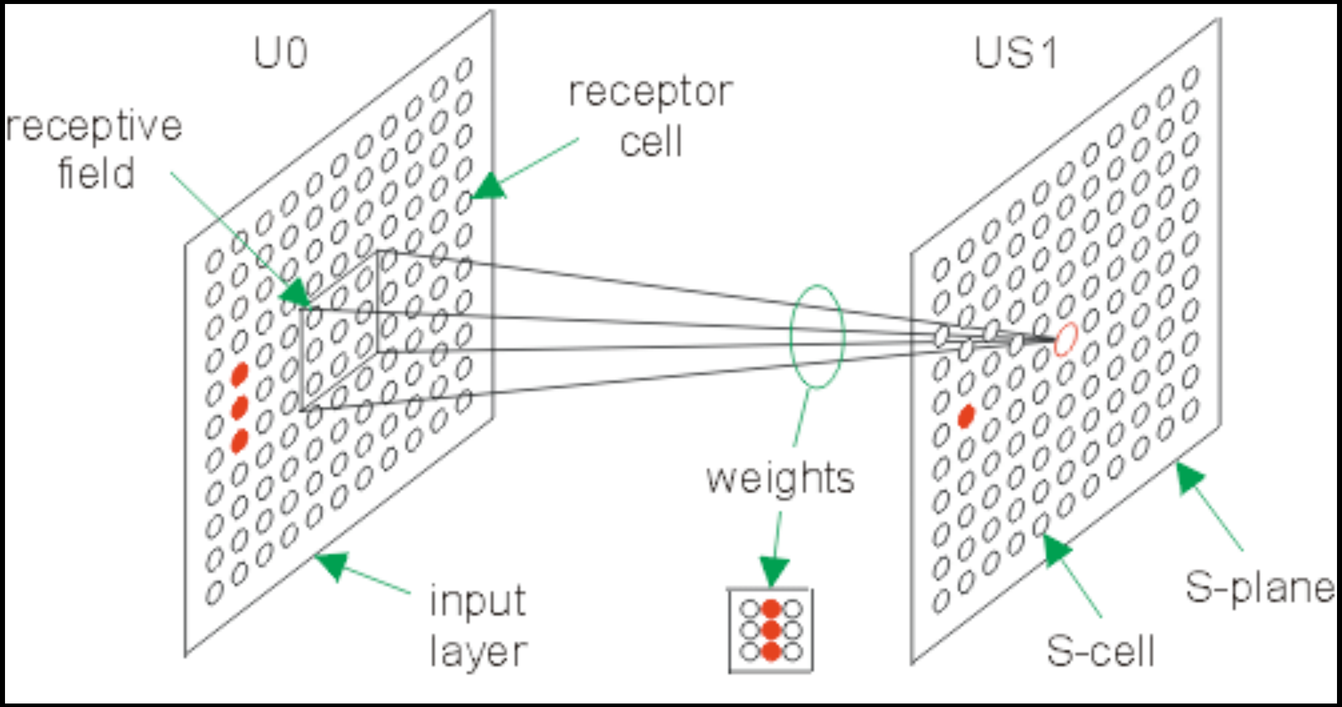
- each layer has k *S-planes*
- each S-plane feeds into its own *C-plane*
- *V_S-planes* and *V_C-planes* inhibit S-planes and C-planes, respectively

Design - S-plane

- cells in each plane are arranged in a 2-d grid
- each S-cell looks at a sliding 2-d window in the previous layer
- S-cells in a plane all have the same coefficients (i.e. they are convoluted), but look at a different window



Design - S-plane

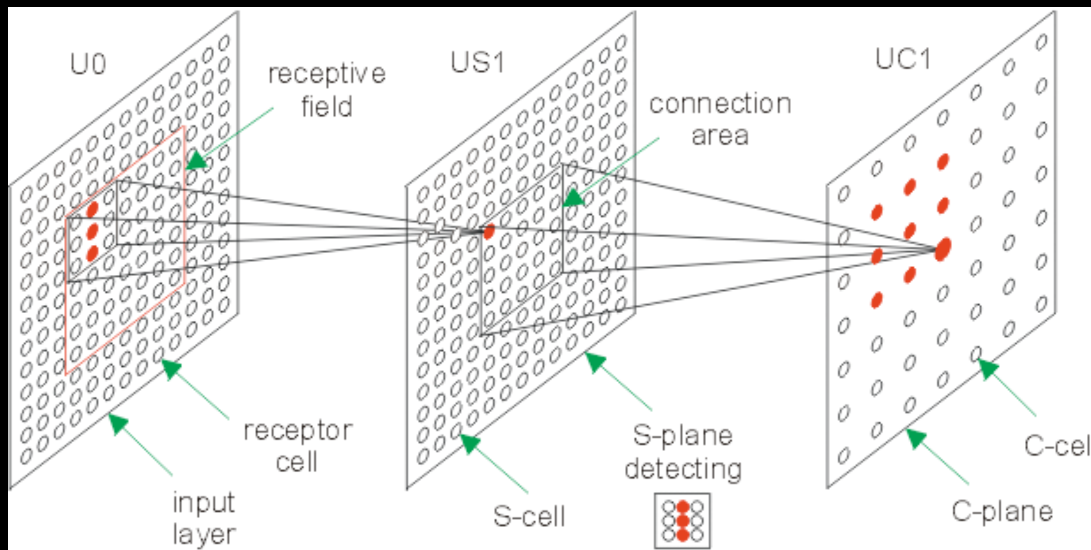


Design - S-plane

Design - C-plane

- an S-plane learns to recognize one feature no matter where it is
- the corresponding C-plane ORs a region of S-cells to recognize that feature anywhere in that region (achieving a level of shift invariance)
- C-cell input weights are not learned

Design - C-plane

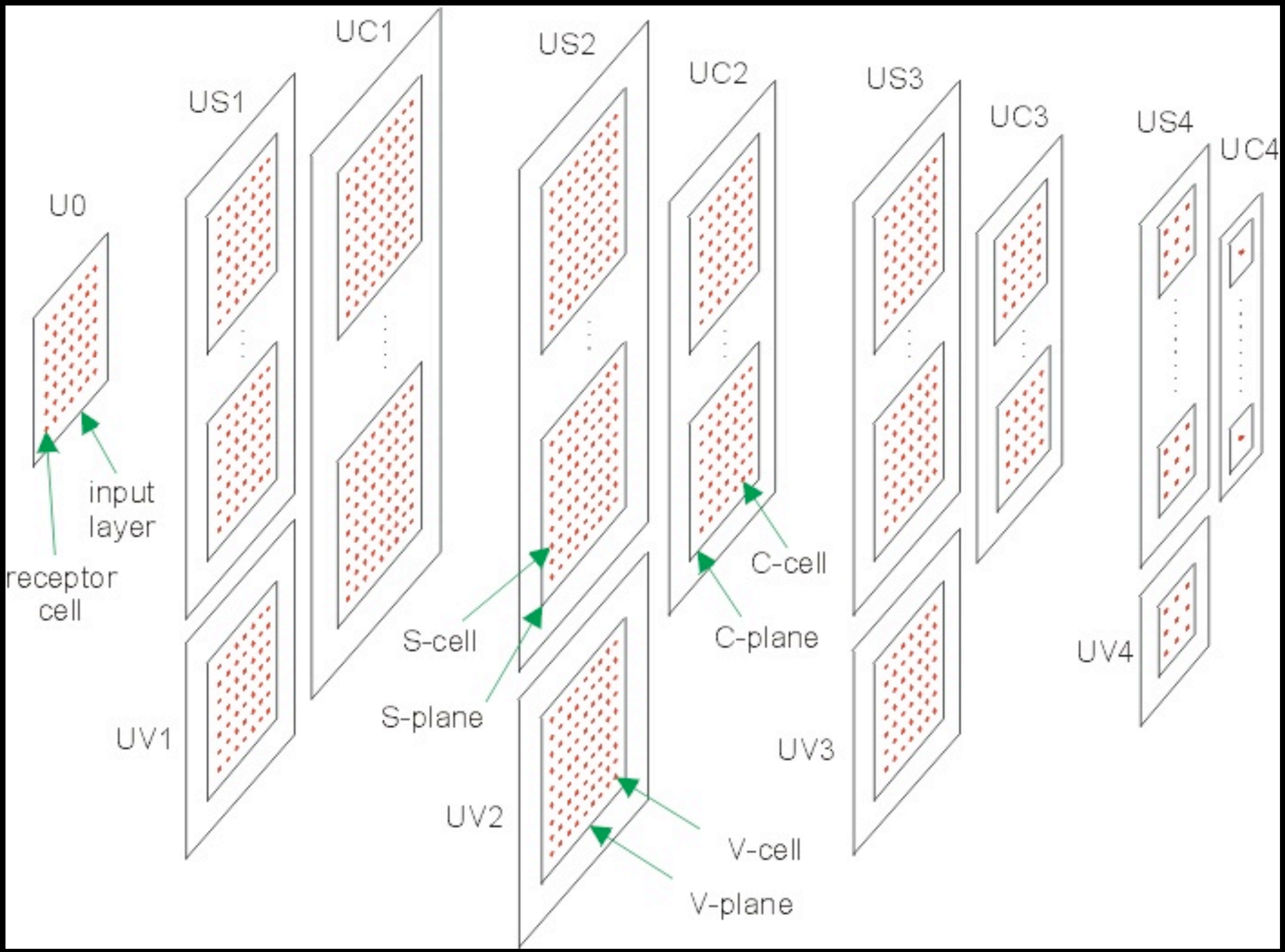


Design - C-plane

Design - Output

- In the final layer, each C-plane has only one cell, which effectively looks at the entire image

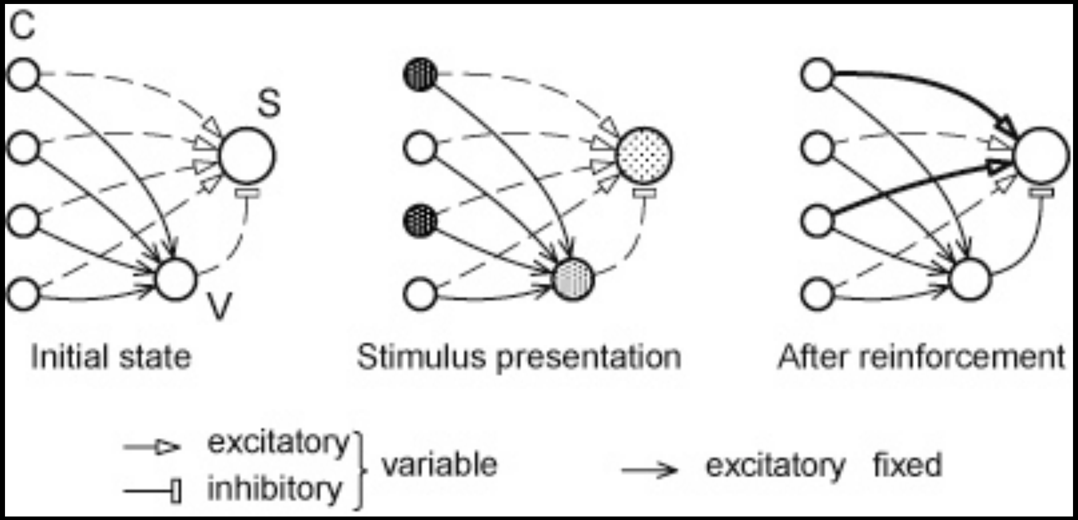
Design -
All Together Now



Learning

Learning - Cognitron

- weights get initialized with small positive values
- for each training instance, if a cell is the most active in its region *and* in its plane, then its active weights get reinforced
- show the same few training instances over and over again



Learning - Cognitron

Learning - Cognitron

- similar to Hebbian learning (“fire together, wire together”), but only one cell maximum per layer and region gets reinforced
- note: we’re not doing gradient descent, and not minimizing any objective

Learning

- mostly glossing over inhibitor cells and and mathematical formulas. refer to paper
- math works out so that an S-cell's weights directly correspond to the feature it is recognizing, and activation = cosine similarity

Learning - Example Weights

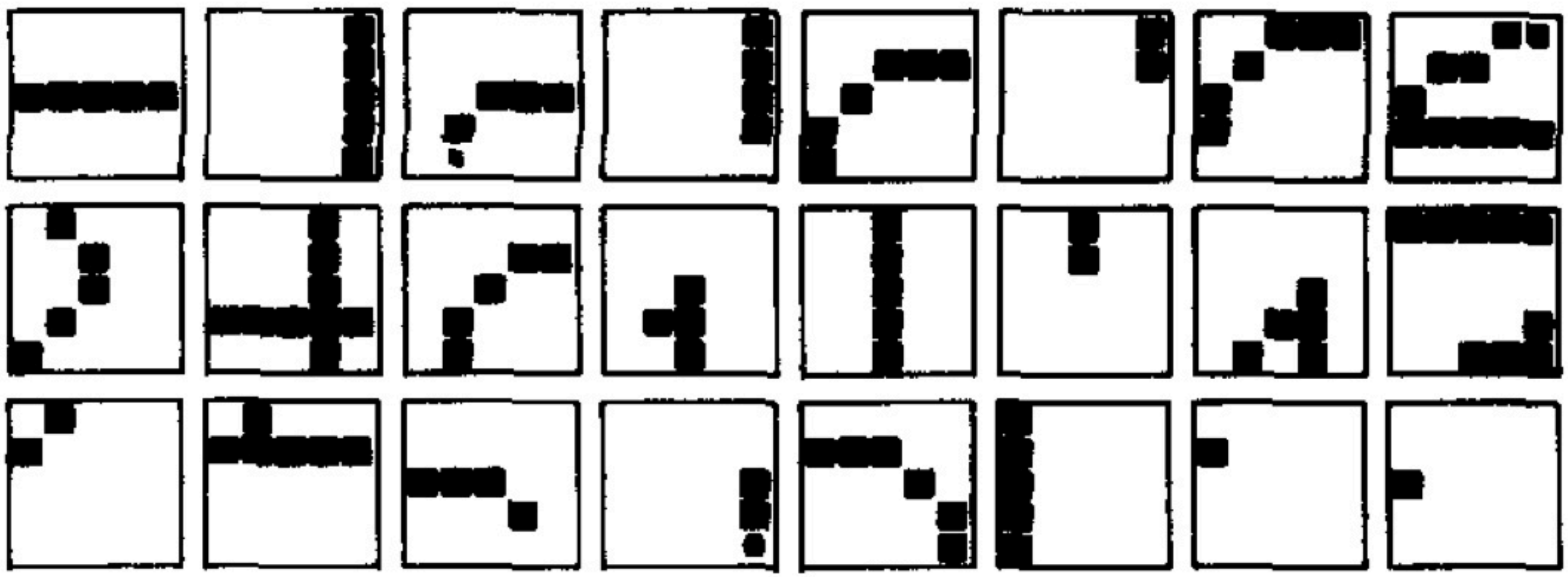


Fig 12 Receptive fields of the cells of each of the 24 S-planes of layer U_{S1}, which has finished learning

Learning - Example Activations

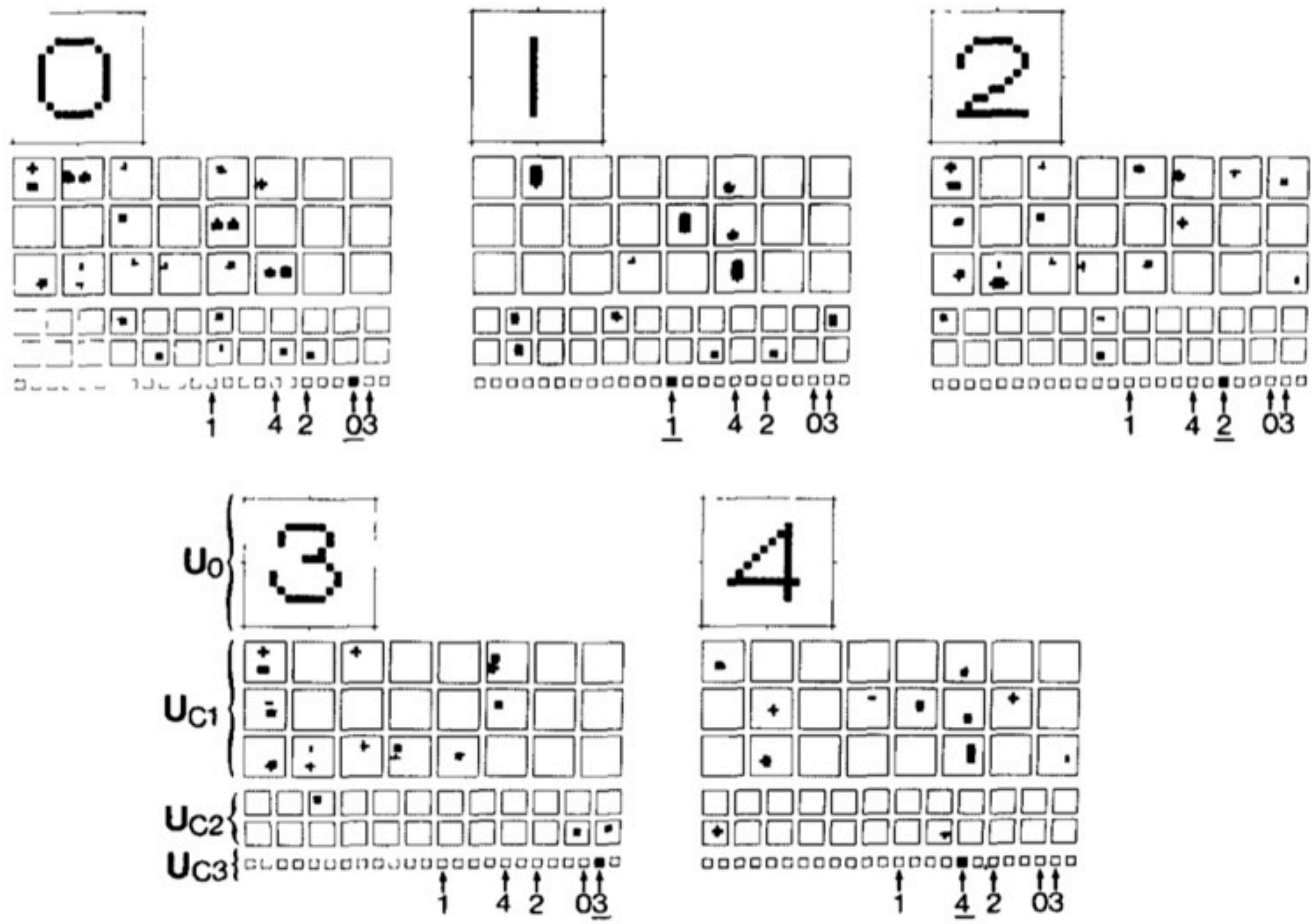


Fig 10 Response of the cells of layers U_0, U_{C1}, U_{C2} and U_{C3} to each of the five stimulus patterns

Discussion

Discussion

- Experiment was a toy problem. Does this work on anything real?
- Does it need to be so complicated?

Problems -
Not Really Scale-Invariant

- the amount of shift/deformation-invariance is hardcoded into the structure, by how big a region each C-cell covers e.g.
- intuitively: only one training example is used for each digit; how could it possibly be learning what kinds of deformations to allow?
- empirically demonstrated by Barnard and Casasent, 1990

References

- Barnard, E., and Casasent, D. "Shift Invariance and the Neocognitron." Neural Networks 3, no. 4 (1990): 403–410.
- Fukushima, K., and Miyake, S. "Neocognitron: A New Algorithm for Pattern Recognition Tolerant of Deformations and Shifts in Position." Pattern Recognition 15, no. 6 (1982): 455–469.
- figures from http://www.kiv.zcu.cz/studies/predmety/uir/NS/Neocognitron/en/index.html

Questions?