A logical calculus of the ideas immanent in nervous activity

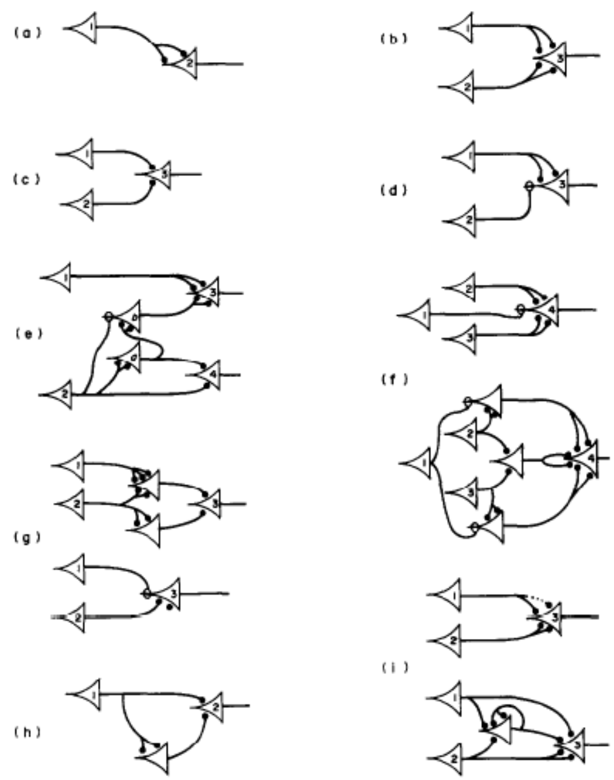


Figure 1. The neuron c_i is always marked with the numeral i upon the body of the cell, and the corresponding action is denoted by "N" with i s subscript, as in the text:

(a) $N_2(t) . \equiv . N_1(t-1);$

(b) $N_3(t) . \equiv . N_1(t-1) \vee N_2(t-1);$

(c) $N_3(t) . \equiv . N_1(t-1) . N_2(t-1);$

(d) $N_3(t) . \equiv N_1(t-1) . \sim N_2(t-1);$

(e) $N_3(t) : \equiv : N_1(t-1) . \vee . N_2(t-3) . \sim N_2(t-2);$

$N_4(t) . \equiv . N_2(t-2) . N_2(t-1);$

(f) $N_4(t) : \equiv : \sim N_1(t-1) . N_2(t-1) \vee N_3(t-1) . \vee . N_1(t-1).$

$N_2(t-1) . N_3(t-1)$

$N_4(t) : \equiv : \sim N_1(t-2) . N_2(t-2) \vee N_3(t-2) . \vee . N_1(t-2).$

$N_2(t-2) . N_3(t-2);$

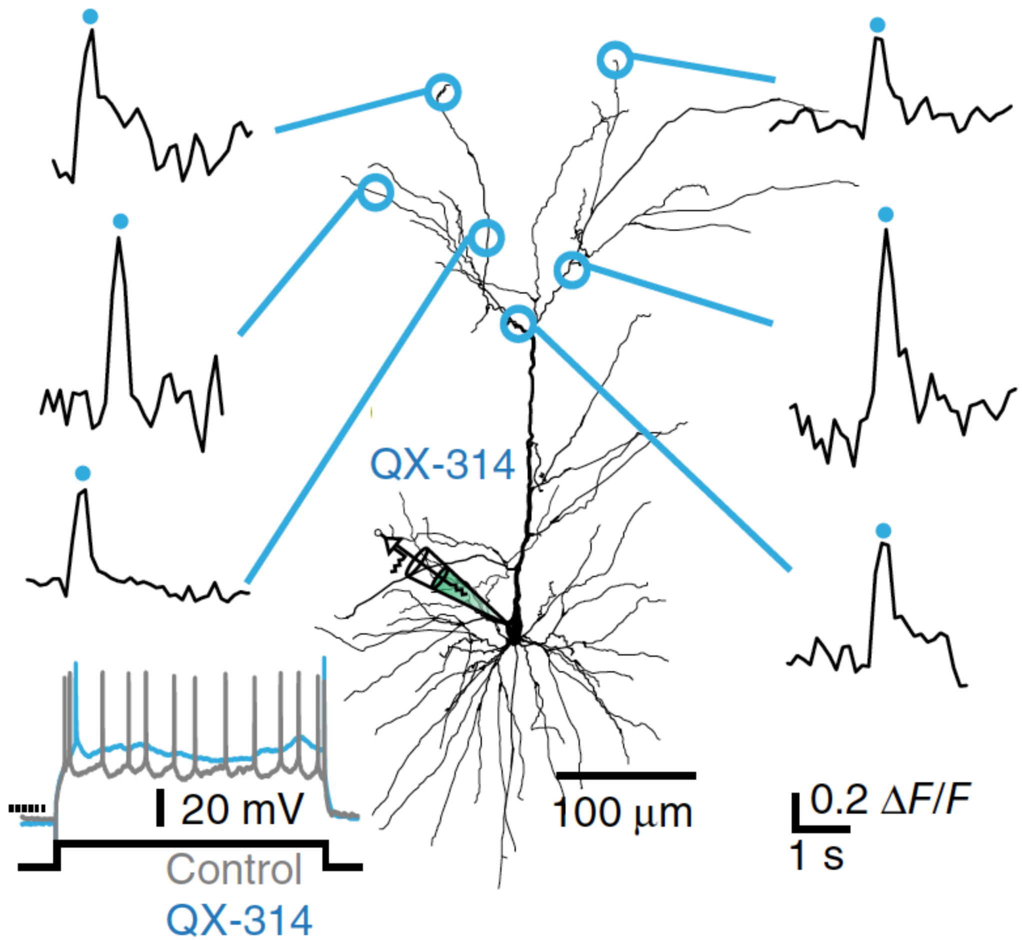
(g) $N_3(t) . \equiv . N_2(t-2) . \sim N_1(t-3);$

(h) $N_2(t) . \equiv . N_1(t-1) . N_1(t-2);$

(i) $N_3(t) : \equiv : N_2(t-1) . \vee . N_1(t-1) . (Ex)t-1 . N_1(x) . N_2(x).$

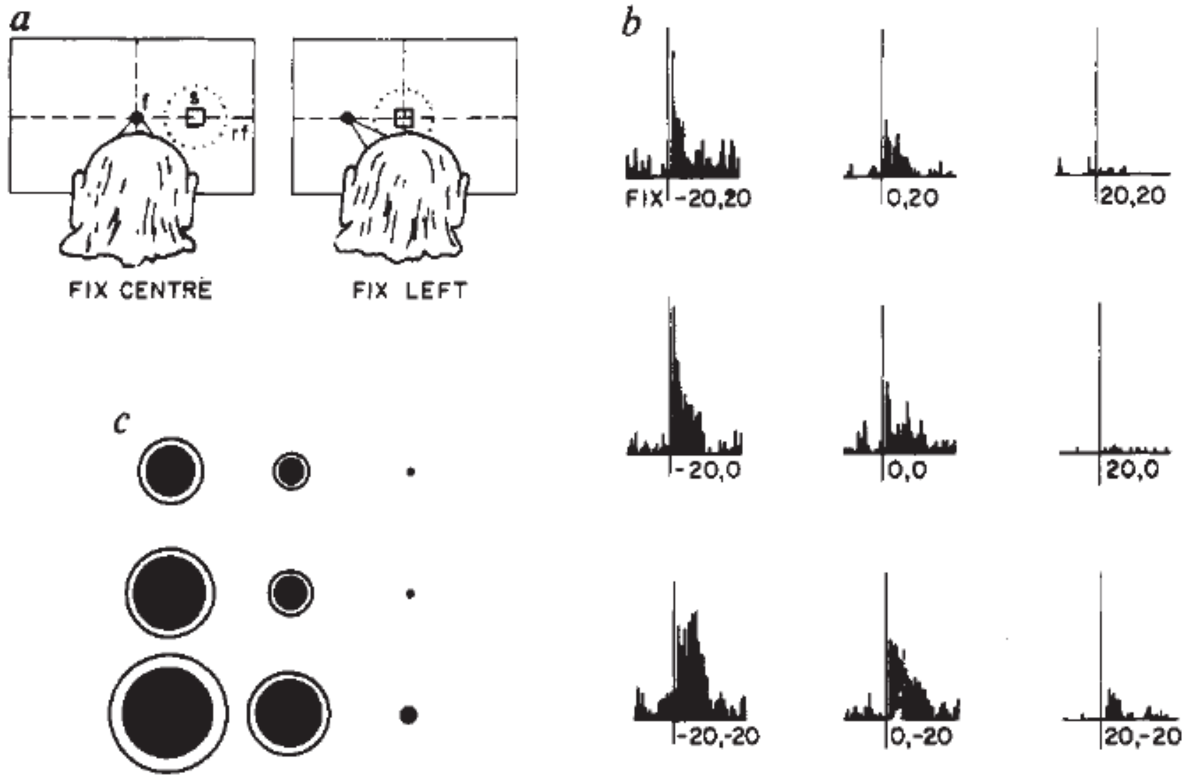
McCullocch and Pitts (The Bulletin of Mathematical Biophysics, 1943)

SIngle (complex) cells as Perceptrons



Palmer, Shai, Reeve, Anderson, **P**aulsen **and** Larkum (Nature Neuroscience 2014)

Multilayer perceptron to simulate responses in parietal cortex
(mixture of gaze direction and retinotopic location of an object)



Zipser and Andersen (Nature 1988)

Experimental data

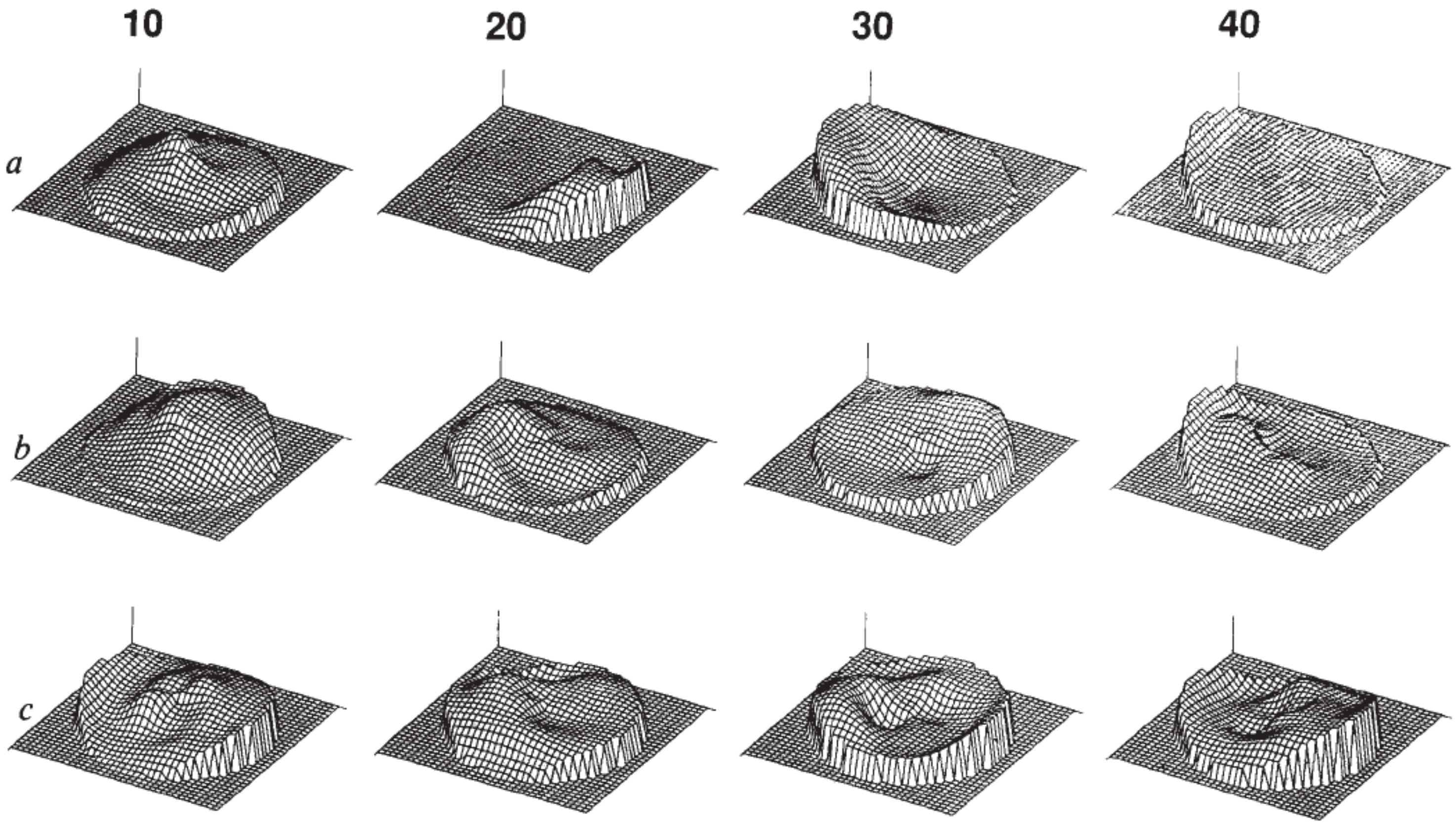


Fig. 2 The receptive fields of spatially tuned neurons from area 7a, arranged in rows with the eccentricity of the field maxima increasing to the right, and in columns with the complexity of the fields increasing downwards. Receptive fields were sampled at 17 radially spaced points, with one sample taken at the centre of the field, and four samples taken on each of four circles of radius 10, 20, 30 and 40 degrees. All the fields in row *a* have single peaks. Those in row *b* have a single large peak but some complexities in the field. The fields in row *c* are the most complex with multiple peaks. The data have been normalized so that the highest peak in each field is the same height.

Zipser and Andersen (Nature 1988)

Model "hidden units"

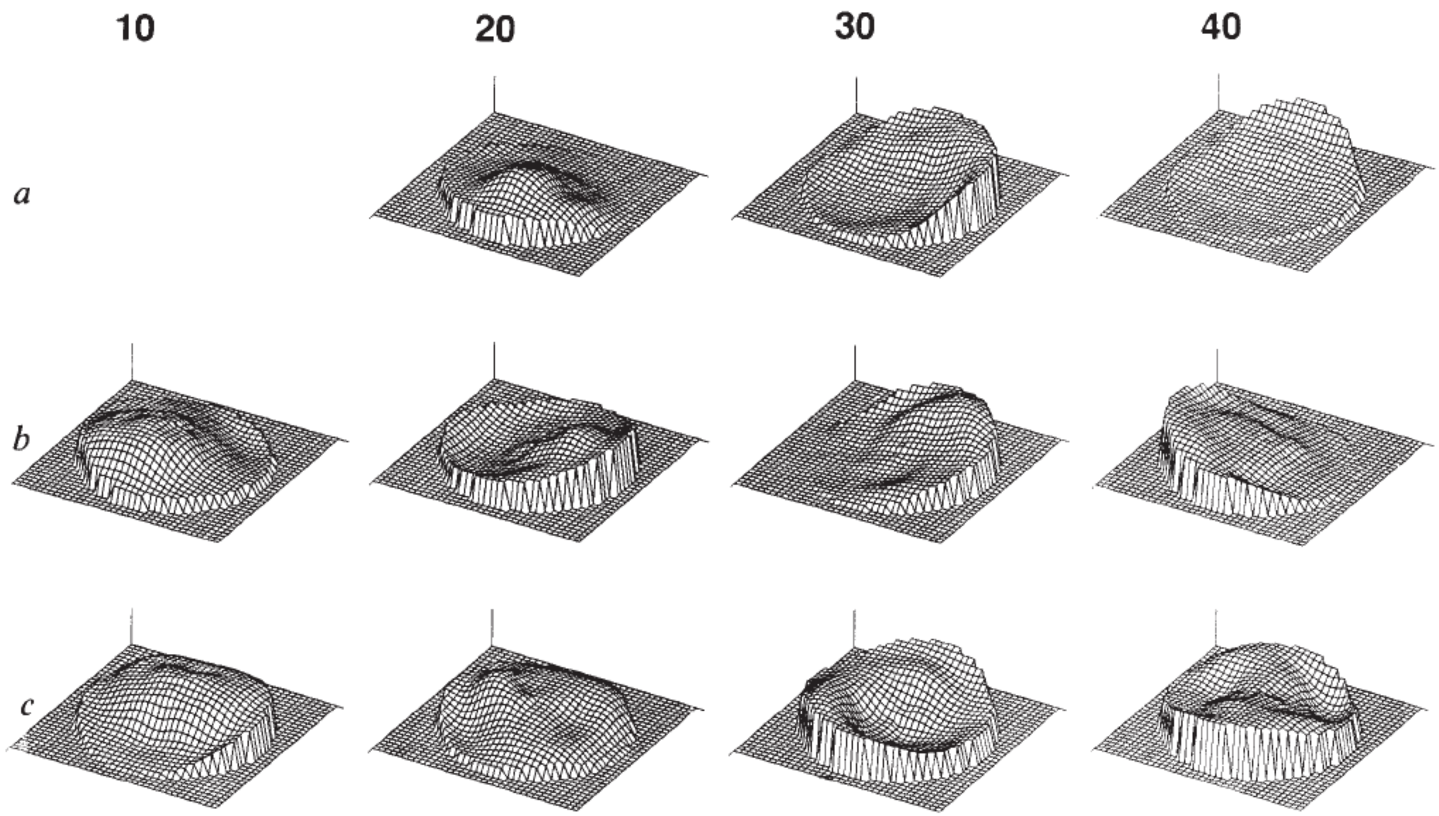
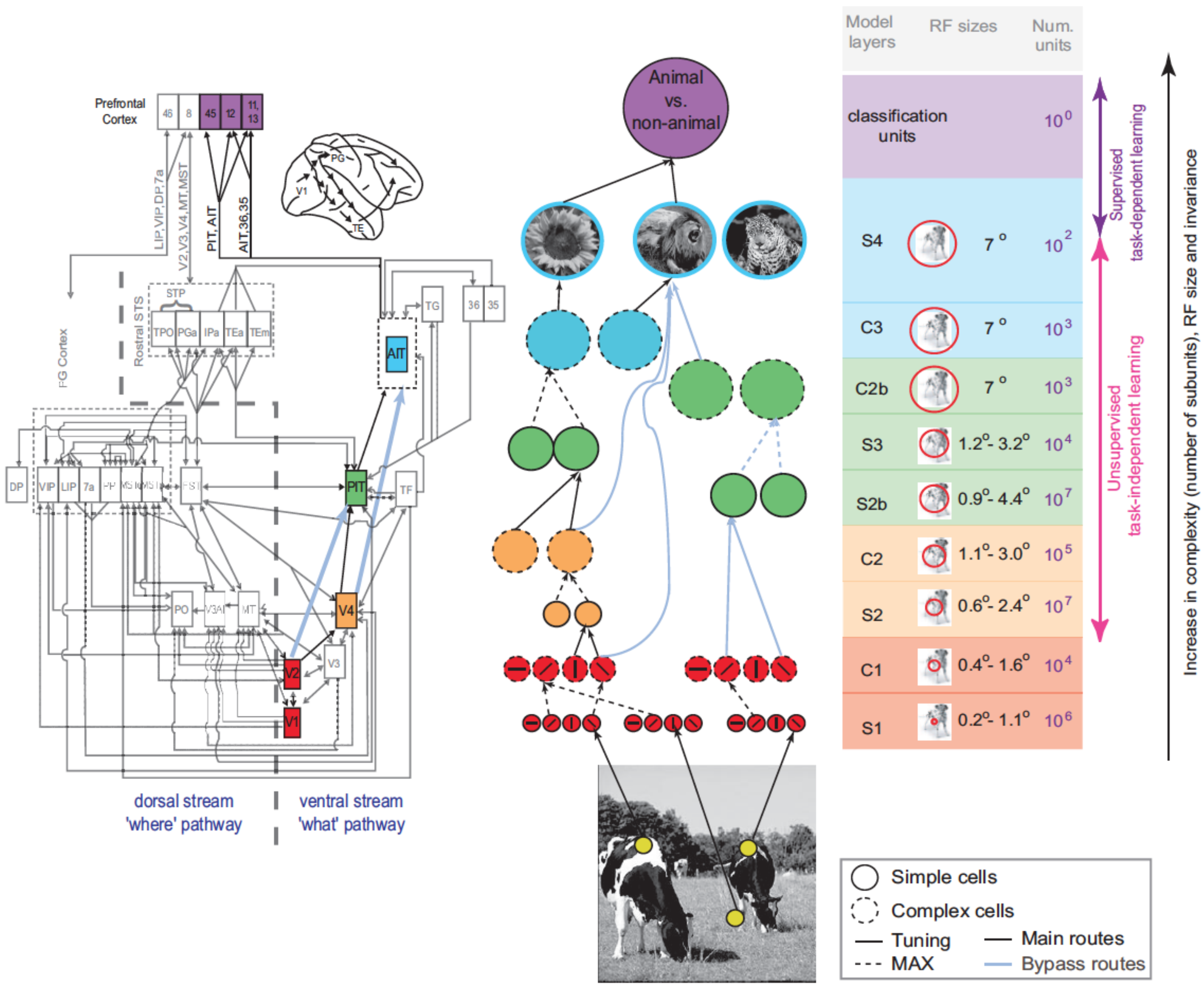


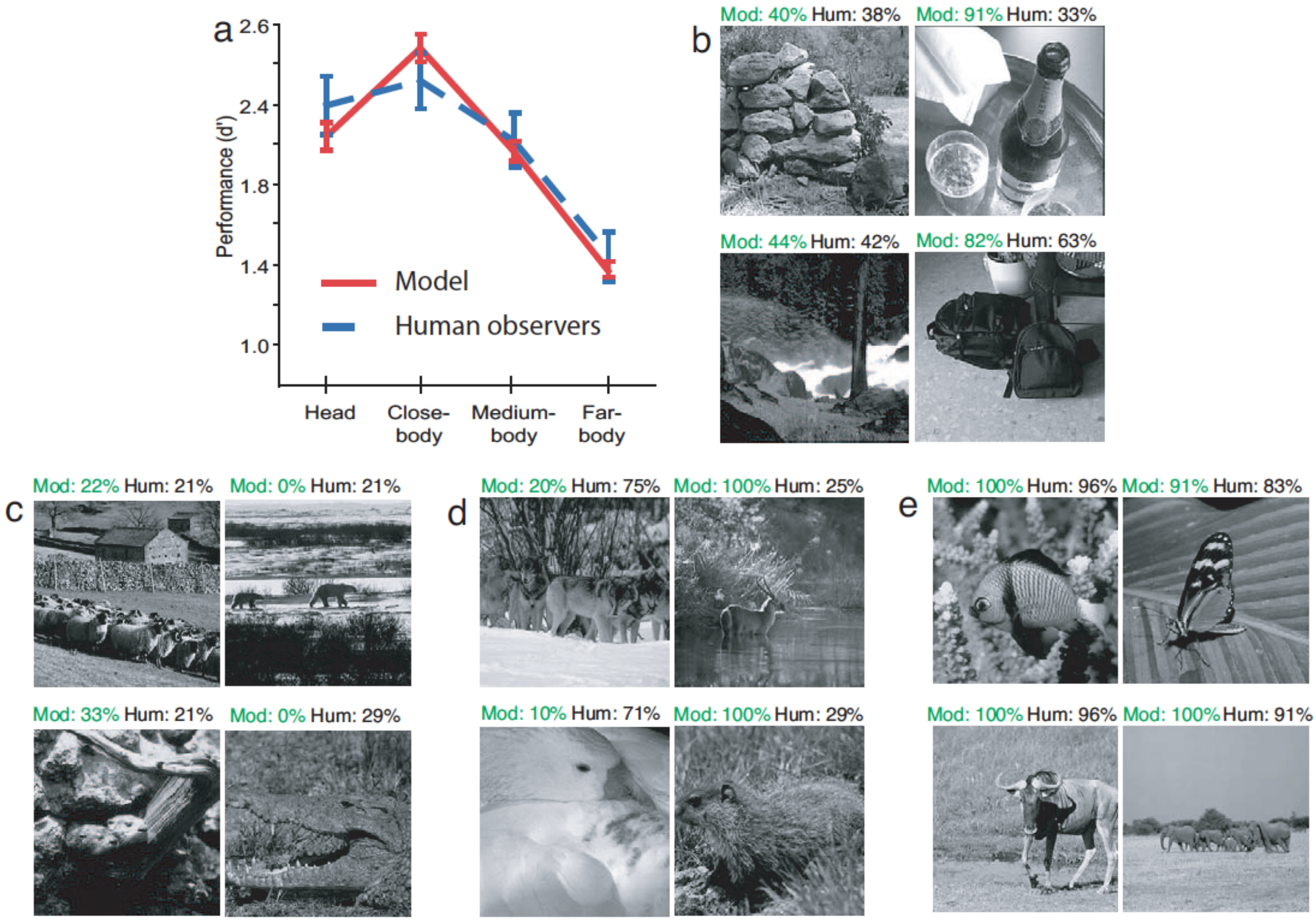
Fig. 5 Hidden unit retinal receptive fields generated by the back propagation model. These plots were generated by holding the eye-position input to the network constant and simulating visual stimulation at the same 17 retinal positions used in the experiments on area 7a. The hidden unit activities were normalized and plotted in the same way as the experimental data shown in Fig. 3. The data shown here are from a series of 4 training sessions using networks with 25 hidden units and the monotonic format output. Similar results were obtained for the gaussian format output. All the fields, except for C-10, C-20 and C-30, are from networks that have received 1,000 learning trials. The remaining three are from untrained networks, resulting only from the random synaptic weights assigned at the start of a training run. Very complex fields are only rarely found in trained networks. No hidden unit with a single peak at 10 degrees appeared in this data set and such units are very rare in trained networks. No spatially tuned neurons with central receptive fields were found in area 7a, and no such fields appeared in the trained model. But central receptive fields are found among the visual neurons in 7a, and this kind of unit was among those used as input to the model network.

Zipser and Andersen (Nature 1988)

Multilayer perceptron to recognize presence of an animal - or not - in a picture

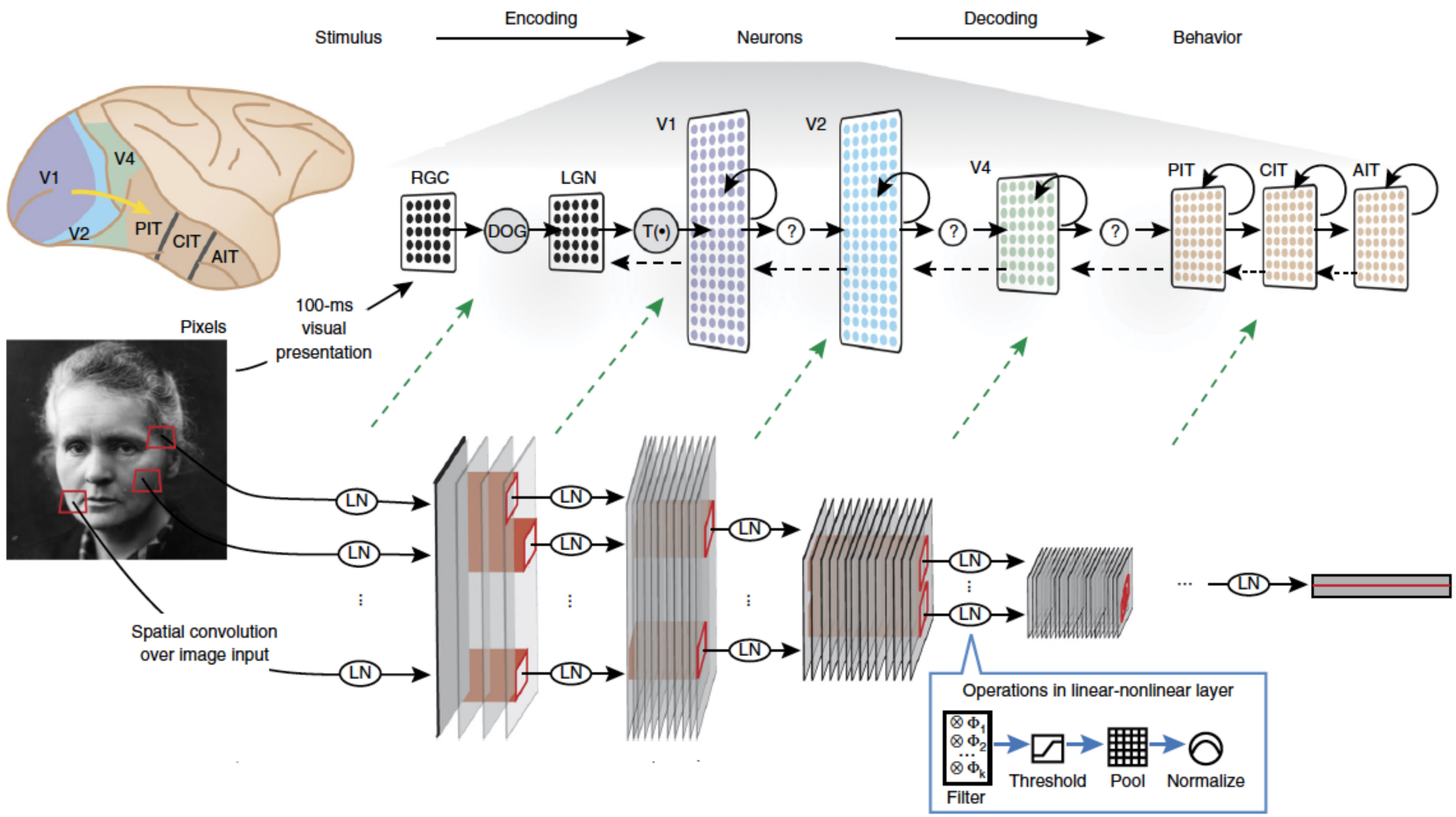


Serre, Oliva and Poggio (PNAS 2007)



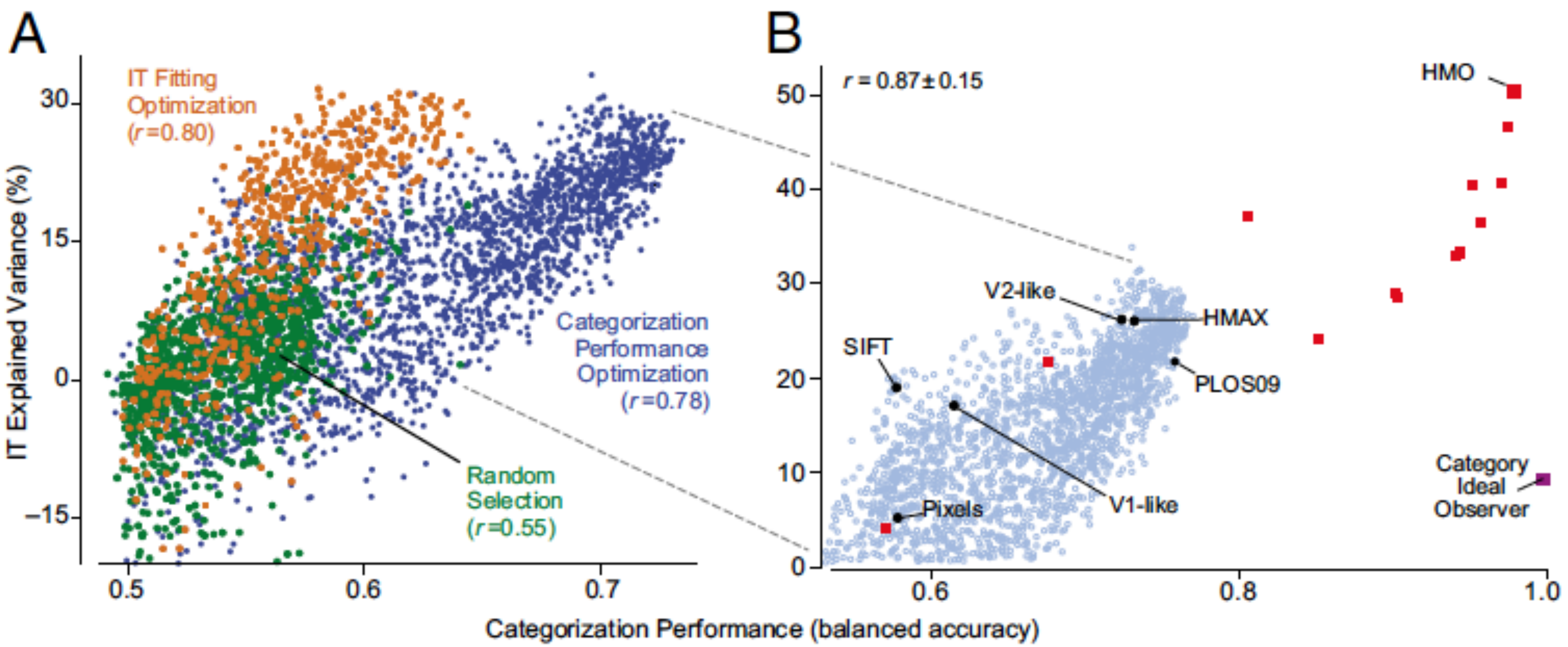
Serre, Oliva and Poggio (PNAS 2007)

Improved realization of object discrimination in multilayer network models of vision



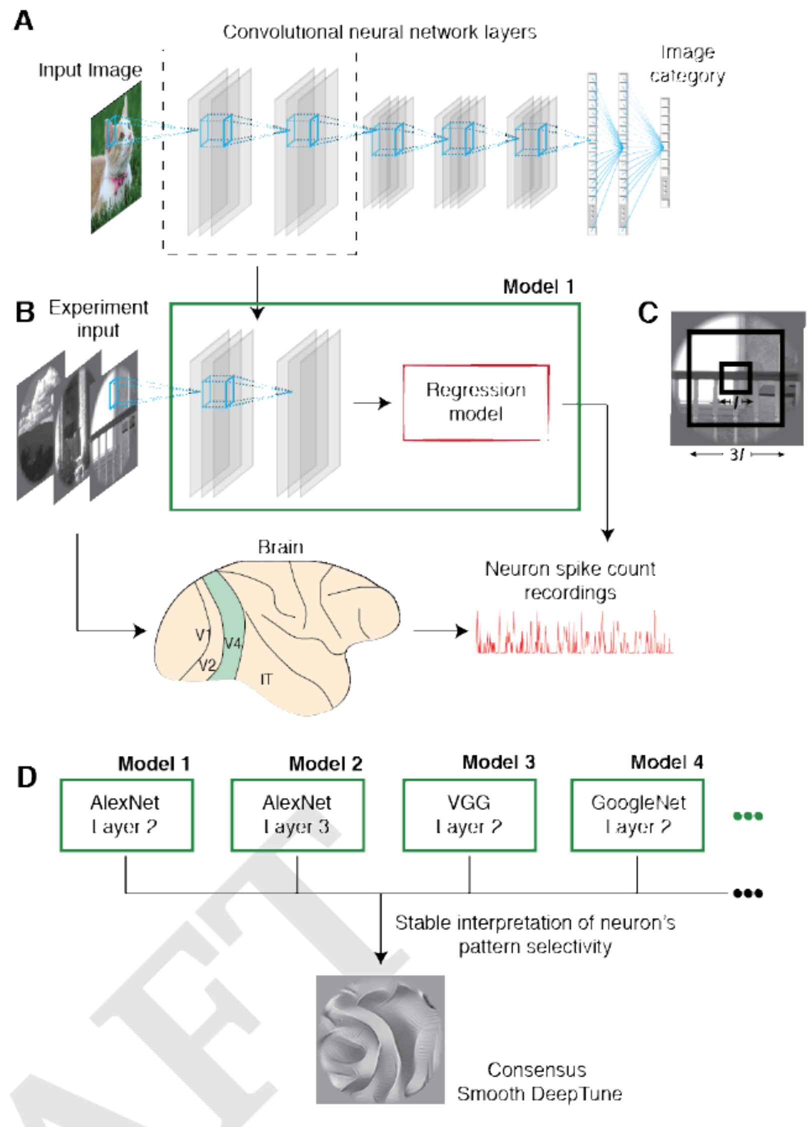
Yamins, Hong, Cadieu, Solomon, Seiberta and DiCarlo (PNAS 2014)

'... there is a strong correlation between a model's performance on a challenging high-variation ɔbject recognition task and its ability to predict individual IT neural unit responses."

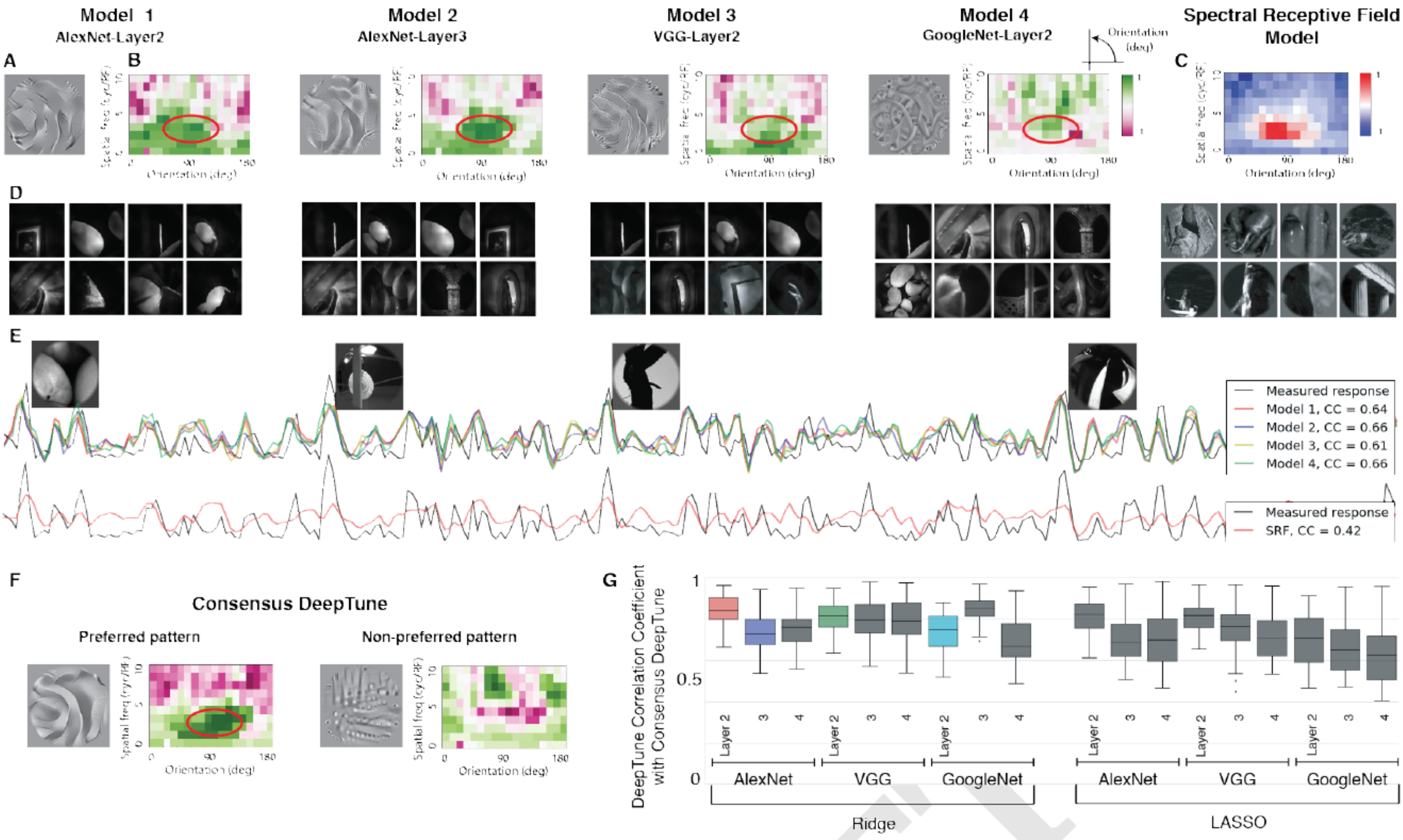


Yamins, Hong, Cadieu, Solomon, Seiberta and DiCarlo (PNAS 2014)

Mixture models of multilayer networks to reproduce spike response



Abbasi-Asla, Chen, Bloniarz, Oliver, Willmore, Gallant and Yua (submitted to PNAS)



Abbasi-Asla, Chen, Bloniarz, Oliver, Willmore, Gallant and Yua (submitted to PNAS)