Project name: **IRENA** (**I**nvariant **R**epresentations **E**xtraction in **N**eural **A**rchitectures)
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Approach

In our proposed solution we aim at a combination of Neuroscience principles, Abstract thinking and Prototyping, towards a solution aiming at bringing the efficiency and robustness of biological intelligence to technical systems that solve real-world problems. We start from the proposed Neuroscientific Research Challenges and propose a novel model and system capable of learning invariant representation.

Preamble

In this project we aim at building an unsupervised learning system that is based on and inspired by our biological intelligence for the problem of learning invariant representations. Mammalian visual systems are characterized by their ability to recognize stimuli invariant to various transformations. With our proposed model, we investigate the hypothesis that this ability is achieved by the temporal encoding of visual stimuli, and why not, other sensory stimuli. By using a model of a multisensory cortically inspired network, we show that this encoding is invariant to several transformations and robust with respect to stimulus variability. Furthermore, we show that the proposed model provides a rapid encoding and computation, in accordance with recent physiological results [9].

Elucidating the mechanisms of invariant pattern recognition is an active field of research in neuroscience [1–5]. However, very little is known about the underlying algorithms and mechanisms. A number of models have been proposed which aim to reproduce capabilities of the biological visual system, such as invariance to shifts in position, rotation, and scaling [6–8]. Starting from these premises, in order to build our approach, we reviewed functional organization in sensory cortical regions - how the cortex represents the world.

We consider four interrelated aspects of cortical organization and computation: (1) the set of receptive fields of individual cortical sensory neurons - the data representations, (2) how interaction between cortical neurons reflects the similarity of their receptive fields - the data composition, (3) the spatial distribution of receptive-field properties - the data hierarchization and (4) how the spatial distributions of different receptive-field properties interact with one another - the cue-integration and correlation learning.

Driven by these principles and the study in [9] which shows how the neurophysiology data are generally well explained by the theory of input-driven self-organization, we explore a cortically-inspired model of cortical maps offering a parsimonious account for a wide range of map-related phenomena, that has the potential to explain phenomena related to the formation of hierarchical invariant representations. We decided to go deeper and address the problem of learning underlying relations behind such transformations by using biologically plausible representation (i.e. population codes) and computation (i.e. competition, cooperation, correlation).

Introducing the core model and system *(qualifiers)*

Using cortical maps as neural substrate for distributed representations of sensory streams, our system is able to learn its connectivity (i.e., structure) from the long-term evolution of sensory observations. This process mimics a typical development process where self-construction (connectivity learning), self-organization, and correlation extraction ensure a refined and stable representation and processing substrate, as also shown in [10]. Following these principles, we propose a model based on Self-Organizing Maps (SOM) [11] and Hebbian Learning (HL) [12] as main ingredients for extracting underlying correlations in sensory data, the basis for subsequently extracting invariant representations. Our vision is that biological systems process visual input using a distributed representation, with different areas encoding different aspects of the visual interpretation. While current engineering habits tempt us to think of this processing in terms of a pipelined sequence of filters and other feed-forward processing stages, cortical anatomy suggests quite a different architecture, using strong recurrent connectivity between visual areas.

Starting point and motivation

Interestingly enough we started from the challenges that Merck set up in the Neuroscience track.

For motivating the use of SOM we started from the challenge quote: *"[...] the 'location neurons' behave similar to the vector quantization algorithm [...], i.e. the 'location neurons' would realize the same mechanism which is also conjectured to lead to invariant representations!"*.
In order to address the "specialization" of the neurons we used SOM, which is extending the basic process in Vector Quantization (i.e. competition, Winner-Take-All (WTA)) by joining it with cooperation in updating the neural weights (i.e. Soft-WTA). This will allow for a topological representation of the input space in the latent space of representation, such that close inputs are mapped closed in the latent space.
Moreover, SOM are responsible for extracting the statistics of the incoming data and encoding sensory samples in a distributed activity pattern. This activity pattern is generated such that the neuron closest to the input sample, in terms of its preferred value, will be strongly activated. Activation decays as a function of distance between input and preferred value. Using the SOM distributed representation, the model learns the boundaries of the input data, such that, after relaxation, the SOM provide a topology preserving representation of the input space. We extend the basic SOM, introduced in [11], in such a way that each neuron not only specialises in representing a certain (preferred) value in the input space, but also learns its own sensitivity (i.e., tuning curve shape). Using this mechanism, the model optimally allocates resources (i.e., neurons): a higher amount to areas in the input space which need a finer representation; and a lower amount for those areas that don't. This feature emerging from the model is consistent with recent work on optimal sensory encoding in neural populations [13]. This claims that, in order to maximise the information extracted from the sensory streams, the prior distribution of sensory data must be embedded in the neural representation.

For motivating the use of HL we started from the challenge quote: *"[...]Interestingly, this 'OR' operation is exactly what one needs when creating equivalency classes, so this hints at another connection to our conjectured algorithm for invariant representations [...]"*.
In order to address the underlying transformations / mathematical operations performed in neural circuitry, we employed a biologically plausible model that links the field of equivalence classes to accounts of Hebbian learning and categorization [14], namely HL. The second component of our model is the unsupervised Hebbian linkage, more precisely a covariance learning rule akin to the ones introduced in [12]: a fully connected matrix of synaptic connections between neurons in each input SOM, such that the projections propagate from presynaptic units to postsynaptic units in the network. Using an all-to-all connectivity pattern, each SOM unit activation is projected through the Hebbian matrix. The Hebbian learning process is responsible for extracting the co-activation pattern between the input layers (i.e., SOMs) and for eventually encoding the learned relation between the sensors. The effective correlation pattern encoded in a matrix, imposes constraints upon possible sensory values. Moreover, after the network converges, the learned sensory dependency will make sure that values are "pulled" towards the correct (i.e., learned) corresponding values, will neglect outliers, and will allow inferring missing sensory quantities.

Core model

In the following subsection we give a brief overview on the underlying mechanisms in our model. This is also present in the developed demo code (Python code).

In order to give an intuition on the inner workings of the aforementioned mechanisms, we start with a simple bimodal scenario, depicted in Figure 1b, in which the correlation among two sensors is represented by a simple nonlinear relation, e.g., power-law, as depicted in Figure 1a. Here. sensory data can be n-dimensional, yet for simplicity we look at timeseries.

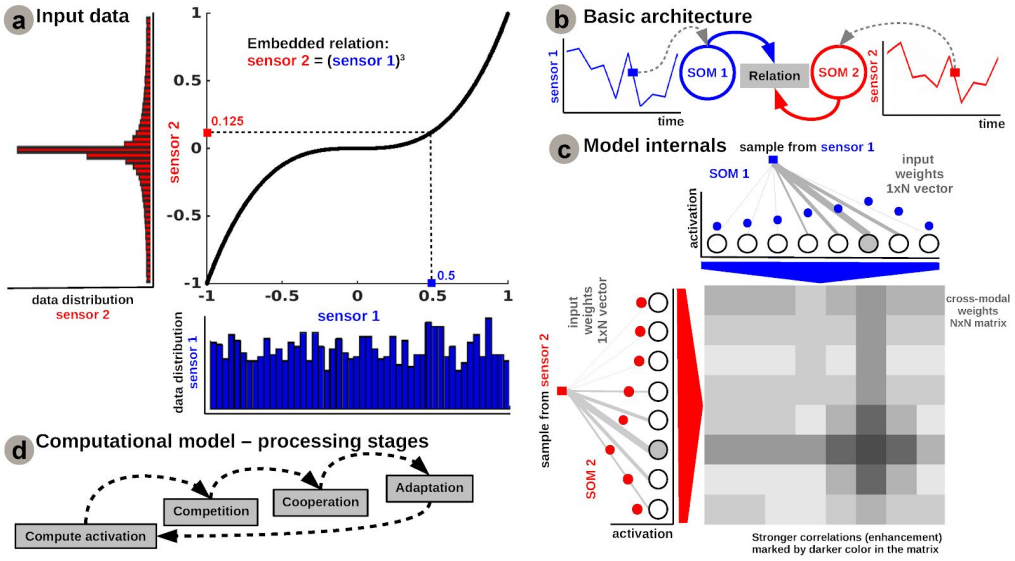

Figure 1. Model architecture. (a) Input data resembling a nonlinear relation and its distribution; (b) Basic architecture; (c) Model internal structure; (d) Processing stages.

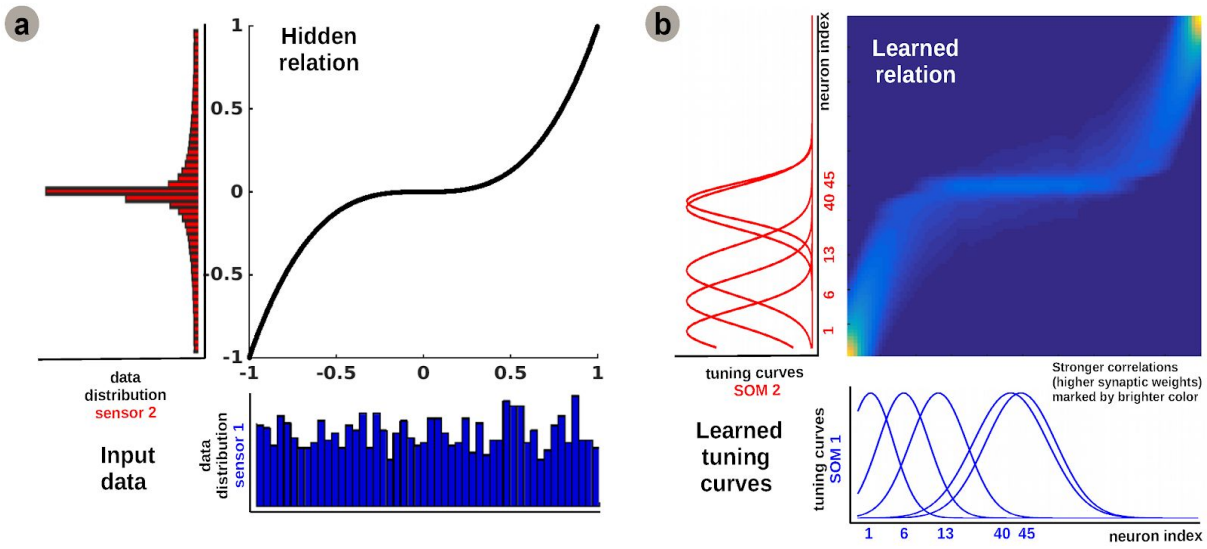

Figure 2. Extracted sensory relation and data statistics using the proposed model: (a) Input data statistics and hidden relation; (b) Learned preferred values and underlying relation.

Recall that, using these mechanisms, the network optimally allocates resources (i.e., neurons): a higher amount to areas in the input space which need a finer representation; and a lower amount for those areas that don't. The unsupervised Hebbian learning process is responsible for extracting the co-activation pattern between the input layers (i.e., SOMs), as shown in Figure 1c, and for eventually encoding the learned relation between the sensors, as shown in Figure 2b. The central panel of Figure 2b demonstrates that connections between uncorrelated (or weakly correlated) neurons in each population are suppressed (i.e., darker color-lower value) while correlated neurons' connections are enhanced (i.e., brighter color-higher value).

Code of the basic implementation is attached with the submission of the project.
NeuroTHIx_IRENA_codebase.zip

A unified framework for invariant representations *(work in the Merck internship)*

In the following section we provide the perspective and extension ideas for in case we pass the qualifiers and will engage with Merck to bring this ideas to life, in a real-world problem of learning invariant representations in visual scenes.

One of the key differences between biological and engineered visual systems is that engineered solutions traditionally use a feed-forward sequence of processing stages and filters, whereas biology (e.g. in primates) uses strong recurrent connectivity between different brain areas which process different types of information in parallel. Understanding this biological style of visual processing could help with the long term technological goal of matching or surpassing the visual capabilities of biological systems. Some key architectural properties that currently are largely unique to biological vision systems include the strong recurrent connectivity between cortical areas, the ability of seemingly weak input to dominate the activity of a multi-area system, and the ability of a distributed representation to arrive at a

coherent interpretation of weak or noisy input. We considered such principles in our model, yet there are still some interesting aspects to develop on top of our initial system.

In order to demonstrate that we are planning to design a system having these properties, which analyzes visual input with a network of recurrently connected SOM (i.e. through HL matrix), as shown in the basic model using SOM and HL. Each map represents a different aspect of the visual interpretation, such as light intensity or optic flow, as shown in Figure 3.

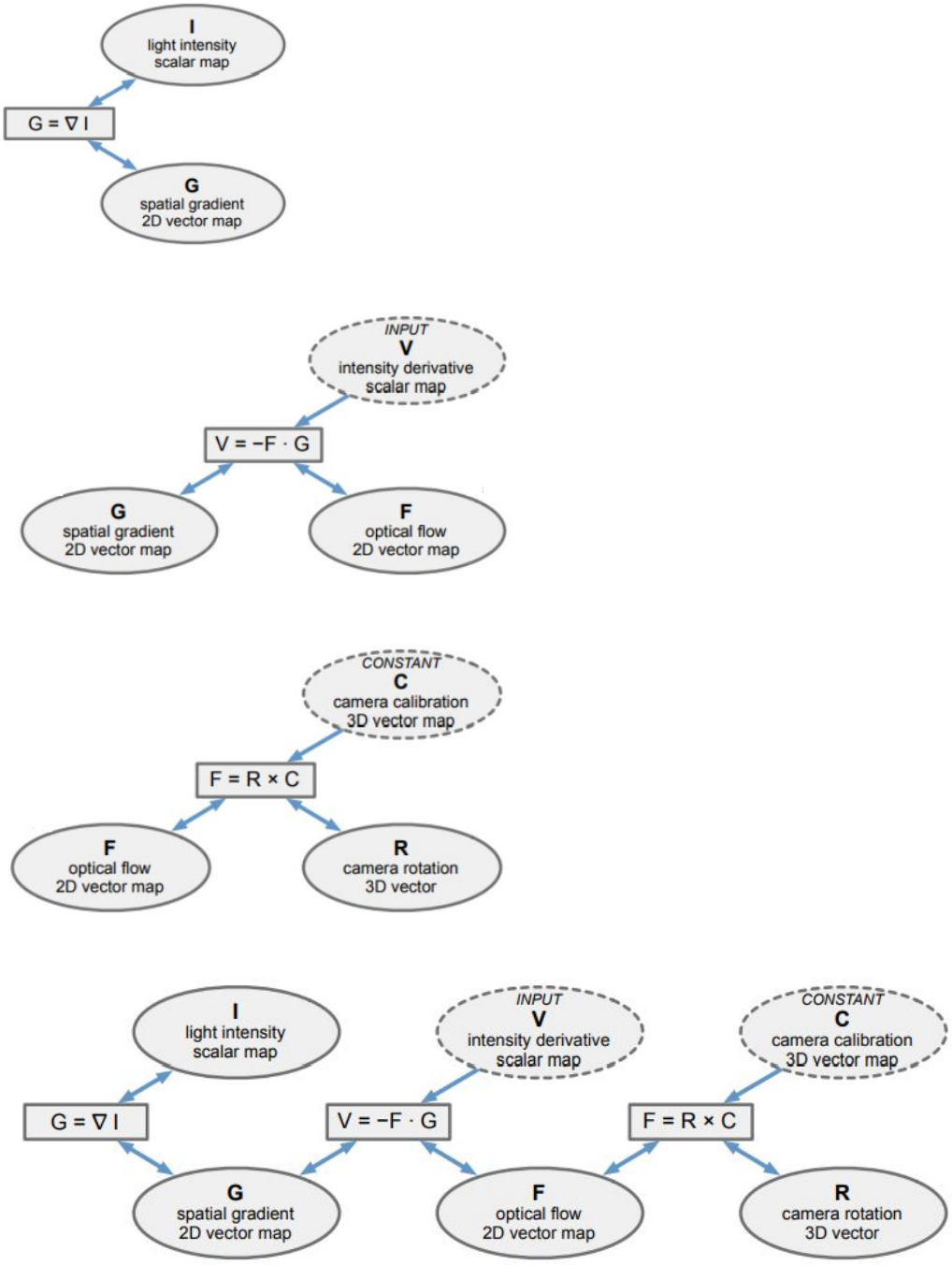

Figure 3: Learning invariant representations in the visual scene: Sample network architectures in which each circle is a sensory quantity and each square is a learnt relation

using our model employing SOM and HL. Incrementally build a complex visual scene understanding from coupling pairs of sensors.

The network could contain, for example, optic flow map F, a light intensity map I, a spatial intensity gradient map G, a temporal intensity derivative map V, a camera calibration map C, and a single (non-mapped) estimate of the three-dimensional rotation R of the camera, which we assume to be fixed at a single point but free to rotate, like an eye in its socket.
As one can see, the relationships between these SOMs, as shown mathematically in the rectangles in Fig. 1, are (i) that G should be the gradient of I, (ii) that spatial variation G in brightness should match time variation V according to the local optic flow F, and (iii) the optic flow F at each point should correspond to the camera motion R with respect to the direction C that the pixel is aimed in. Together, these relations simply express the idea that the input should be explainable in terms of some kind of camera rotation in front of some kind of image.

In our view, such a problem boils down to actually learning invariant representation, such as those relating the SOMs for each sensor through HL. We think that we only have available the input derivative V for our network. Given the input V, it is not possible to simply solve for F and G. The only constraint on the vectors F and G at any pixel is that their scalar product should be -V. This is a very weak constraint, eliminating only one out of the four degrees of freedom in F and G at each pixel. Even if either F or G is known, the other is still underconstrained, being limited only to a line of possibilities. When trying to solve for F, this is known as the aperture problem. The other constraints, namely that the optic flow F at each pixel should be consistent with some overall camera rotation R, and that G should be the gradient of some map I (i.e., a conservative vector field), clearly do not constrain R or I at all. Thus all of the constraints in the system are weak constraints, and it is a priori not clear that the system will be able to find a correct interpretation of the input.

We believe that developing our model to implement such a network is a step towards learning invariant representations. More precisely, this small visual system is simple enough that it is easy to implement and verify for correctness, yet complex enough to solve non-trivial problems such as inferring the grayscale image or the optical flow, as shown in Figure 4. As we might not know what are the mathematical relations describing quantities in our visual scene, we think that our model can learn such mathematical relations directly from the data in an unsupervised manner using SOM and HL.

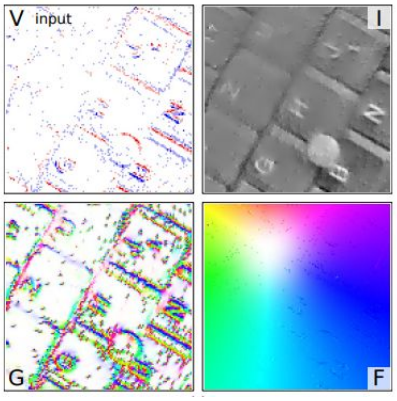

Figure 4: Sample network data after learning the underlying relations

Code implementation of the skeleton of the unified is attached with the submission of the project.

In our preliminary tests, using IRENA for visual scene input, we fed sample, low-res images to the network and basically fed it to the SOM.

Figure 5: Sample image

We assume that the size of input image is 6x6, and the Figure 6 shows the grid representation of input image. We use kernel 3x3 to generate the training data. sliding from left to right and top to bottom in the input image. Thereby we can get 4x3x3 data, as shown in Figure 6.

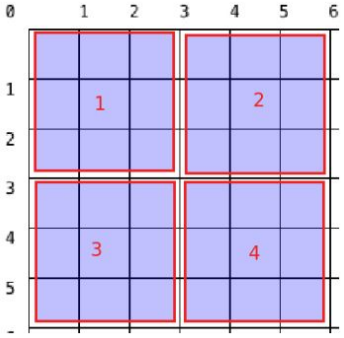

Figure 6: Sample image discretization for training

Now we get 4x3x3 data to training the SOM network.(i.e. assume there are 100 SOM neurons). We feed our network the first 3*3 data and the connection between the input data and the network is shown in Figure 7. We can see that every neuron has 9 weights instead of 1, that is to say our weight matrix is no longer (100,1) but (100,9) . Then we input the pixel values into the network in 9 times and update the weights, the tuning curves using the same update rule used for the one-dimensional data. The only difference is that now each neuron has 9 weights to update(it depends on the size of the kernel).

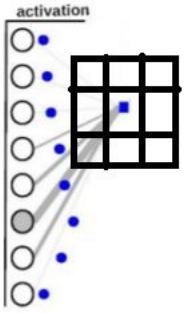

Figure 7: Input - SOM connectivity

After 50 epochs of training of 4x3x3 data we can get the final weights and the final tuning curve, then we can get the encoding results of SOM neurons are as shown in Figure 8.

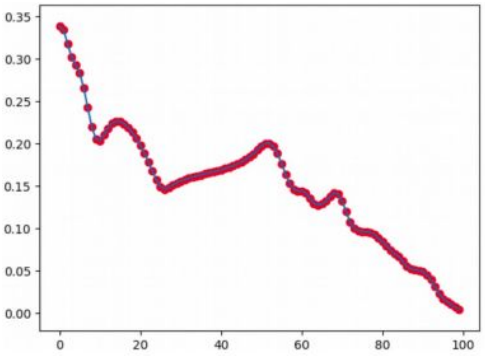

Figure 8: SOM Tuning curves learning

In this Figure 8, the x coordinate represents the neuron number, and y coordinate represents the y coordinate represent the sum of the squares of each neuron weight vector(e.g. $y = w_1^2+w_2^2 +w_3^2 +w_4^2 +w_5^2 +w_6^2+w_7^2 +w_8^2 +w_9^2$). In this experiment we wanted to test the invariant representation capabilities of the SOM that will further contribute to the network ability to also learn more complex quantities in the co-activation pattern. The output is given in Figure 9.

Figure 9: SOM invariant representation test

In the basic pipeline, we used a 3x3 kernel to get the input data like training step and every input data has 9 activation values in each neuron so we add them together as the final activation value. Then we find the neuron position which has the maximum activation value. After getting the neuron position of a input data(size(3x3)) we set the pixel value of the corresponding position in the original image to the same value(value = 2*position). After all 3x3 inputs have been processed in this way we can get the decoding results, as shown in Figure 9. More work can be done in extending IRENA towards more transformations.

Code in NeuroTHIx_IRENA_codebase.zip in /image_input_experiments

Conclusion

Our model provides an answer to the list of questions of the challenge:

• *Is the mechanism which was described above biologically plausible? Can it be connected to anatomical details of the brain?*

Yes, the model uses neural circuits implementing competition and cooperation in topology preserving populations of neurons. Furthermore, is using Hebbian learning as a means to learn correlations among the activation patterns of neurons in the population code. Such circuitry is describing various cortical areas, as we described also in the Preamble section.

• *Can you extend the model towards one which is (1) biologically plausible, (2) shows a relation to the creation of invariant representations (in the spirit of the universal cortical algorithm) and (3) does not only lead to location neurons on a hexagonal grid but to true grid neurons?*

In the basic formulation and implementation we provided, we show that the selected neurally inspired mechanisms have the potential to provide a system for representation and computation to learn invariant representations - as shown in Section “Introducing the core model and system (qualifiers)”. Indeed, there is still an important step to actually frame it to the unified framework for invariant representations - vision emphasized in the Section “Unified framework for invariant representations (work in the Merck internship)”.

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