A Flexible Framework for Cue Integration by Line Attraction Dynamics and Divisive Normalization
Mohsen Firouz1,2,3; Cristian Axenie1; Stefan Glasauer2,3,4; Jörg Conradt1,2,3
1 Neuroscientific System Theory, Technische Universität München; 2 Bernstein Center for Computational Neuroscience, Munich; 3 Graduate School of Systemic Neurosciences, Ludwig-Maximilians-Universität München; 4 Center for Sensorimotor Research at the Department of Neurology, Ludwig-Maximilians-Universität München.

Introduction
The main computations performed by brains involve nonlinear transformations (e.g. sensory-motor transformations), cue integration, or both [1]. For instance, to reach an object by hand, one must configure the arm joints with respect to the visual location of the object. The prefrontal cortex plays a crucial role in such computations. Accessible sensory information is often uncertain and ambiguous, but humans can perceive and estimate the state of the real world, and consequently handle cognitive tasks efficiently despite the presence of noisy signals.

Sensory perception in cortical areas is provided by multiple paths of information targeting uni-modal or multi-modal areas of the brain, which often mutually affect each other. Some simulations of cortically inspired computational frameworks with hand-crafted connectivity have shown how de-noising, inference and sensor perception can possibly be handled by the brain [2]. However, a flexible framework which could learn relationships between cues rather than using fixed networks still needs to be addressed as a challenge, especially in the presence of higher order modalities [3].

An unsupervised framework of relation learning between two interacting populations of neurons was recently proposed, which allows the network to learn arbitrary relations between two sensory variables using biologically motivated learning algorithms like Hebbian learning, homeostatic activity regulation, and winner-takes-all [3]. In this work we suggest a flexible line attractor network that is capable of learning arbitrary non-linear relations between multiple cues using a simple Hebbian Learning principle. We demonstrate that after constructing plastic synaptic weights, the network can perform several principle computational tasks such as inference, de-noising, cue-integration and decision making. Two important features of this framework are its scalability to cases with higher order of modalities and its flexibility to represent smooth functions of relations.

Network Architecture
- The network consists of three input populations (R) and an intermediate layer (A).
- Input variables are encoded as populations of neurons with Gaussian tuning curves.
- All population neurons are reciprocally connected to an intermediate layer (\(W_{jm} = W_{mj}\)).
- \(x_i\) and \(x_j\) are projected to the intermediate layer by a fixed von Mises weighting distribution [2]. They could be arbitrarily related to \(x_i\) by the smooth function \(F(x_i, x_j)\). 
- \(x_i\)'s synaptic connectivity (yellow arrow) is plastic, to realize the relation \(F\) by constructing weights \(W_{in}\) through Hebbian Learning.

Encoding and Network Dynamics
- \(\Phi_i = \frac{\Phi(\mathbf{x}_i, \mathbf{x})}{\Phi(\mathbf{x}_i, \mathbf{x})} + V\) Poisson variability of \(i\) neuron firing rate (c) in response to different stimuli
- \(\Phi(\mathbf{x}_i, \mathbf{x})\) Neuron tuning curve function centered at \(x_i\) (neuron selectivity and mean value of Poisson variability)

- \(\mathbf{x}\): Input variable (stimulus) encoded into population vector \(\mathbf{R}\)
- \(\mathbf{R}\): Spike number per sec (fitting rate) for \(\mathbf{P}\) neuron
- \(\mathbf{v}\): Spontaneous activity rate (1/Hz)
- \(\mathbf{k}\): Intensity of activity (stimulus strength)
- \(\mathbf{r}\): Preferred value for \(\mathbf{P}\) neuron of population vector \(\mathbf{R}\)

Decision Making in Non-invertible Relations \((x_r = x_i^+ + x_i^-)\)
- In case of non-invertible relations it is possible to decide two possible peaks as inverted values.
- If the network is initialized with a tiny negative bias (Fig.4 up-left) for the hidden (unknown) variable, this negative bias helps the network to retrieve the negative peak as perceived value for the hidden variable (Fig.4 up-right).
- In the intermediate layer the bump corresponding to the positive value has been removed (Fig.4 down).

Conclusion and Remarks
In this work a flexible framework of cue integration has been suggested, by which the network can learn a relation between one of the encoded variables as a function of both other variables. The network thereby provides a computational framework for relation satisfaction using attraction dynamics through the generative representation of state populations (variable vectors).

Results exhibit the capability of the network to perform cue integration and inference even for non-invertible and nonlinear functions. It is worth to mention that the optimality of the network strongly depends on network parameters such as tuning curve parameters and divisive normalization parameters. As a consequence, these parameters should be tuned properly.

To avoid emerging double peaks of activity in non-invertible relations, asynchronous evaluation of network dynamics [4] seems to reduce this unavoidable effect without adding additional bias to the network (apart from perceptual importance of bias).

Selected publications: