

Quantifying neural information content: A case study of the impact of hippocampal adult neurogenesis through computational modeling

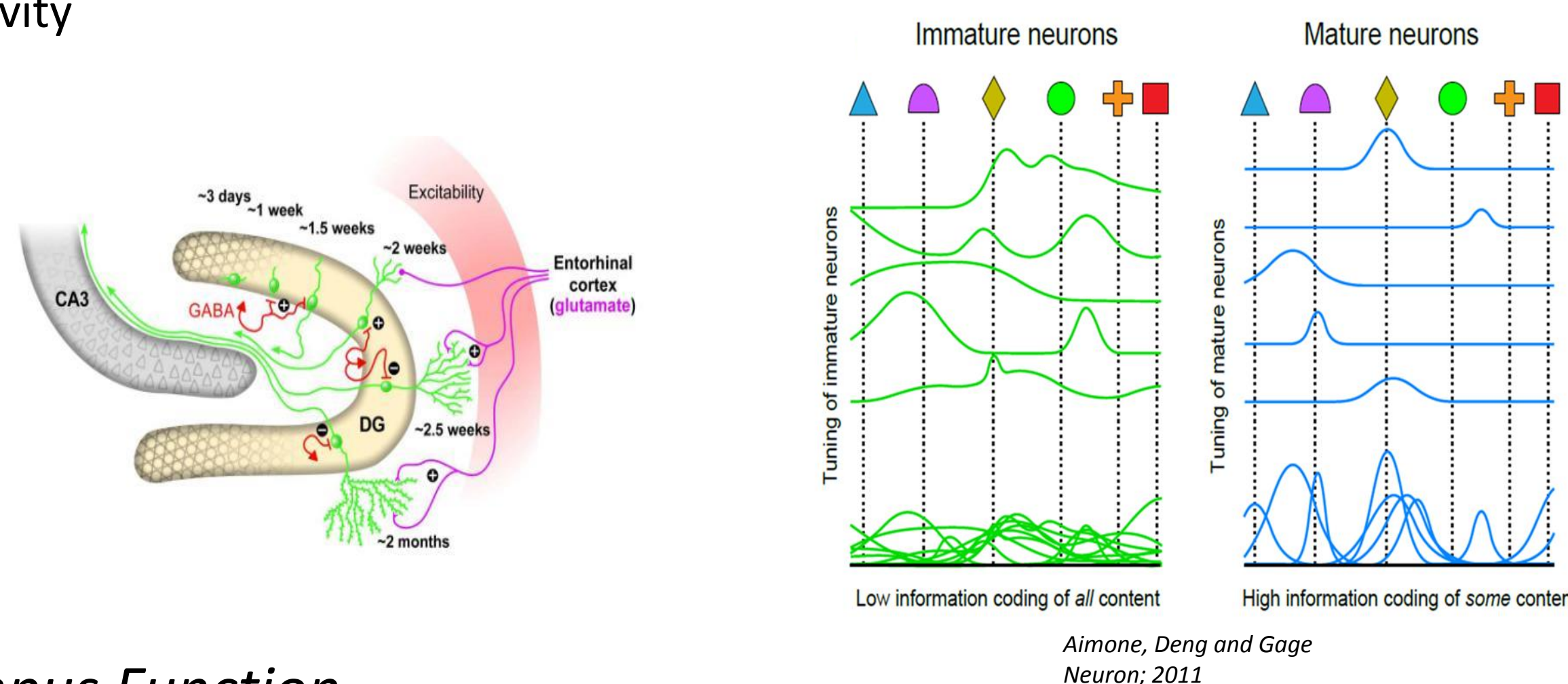
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Background and Approach

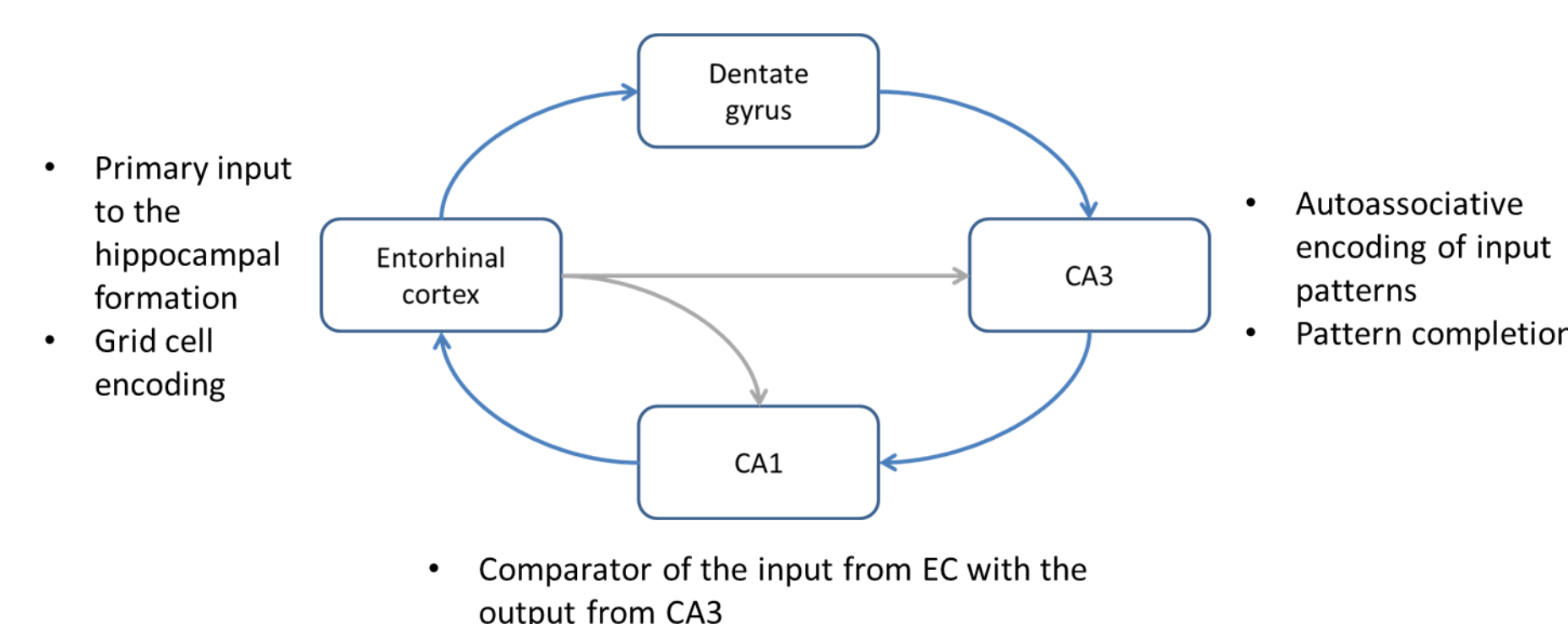
Overview of Adult Neurogenesis

- 1000s of new granule cells integrate into DG monthly
- Only excitatory neurons are born; no new inhibitory neurons in DG
- Process heavily regulated by behavior; for example, running and enrichment increase, stress and aging decrease
- Maturation process extends over months, excitatory and inhibitory pathways develop in parallel
- Young neurons are more “excitable” than mature counterparts due to distinct physiology and connectivity



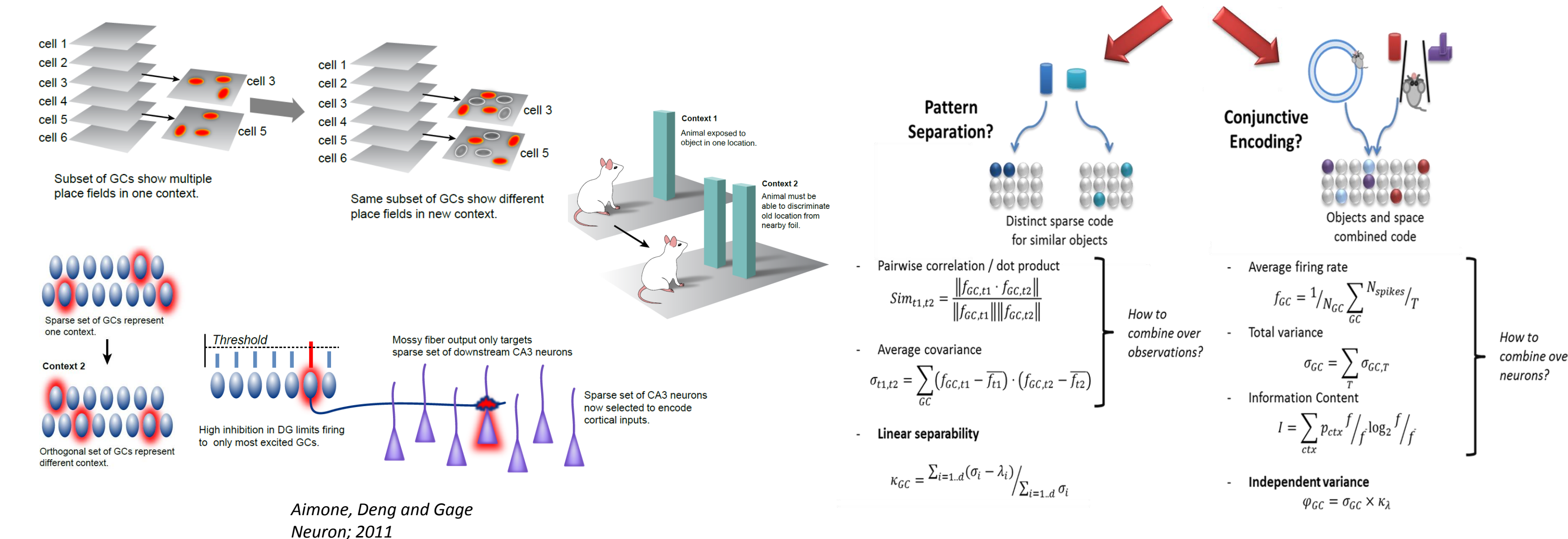
Hippocampus Function

- Proposed to enhance the encoding of new memories by performing pattern separation
- Orthogonalization

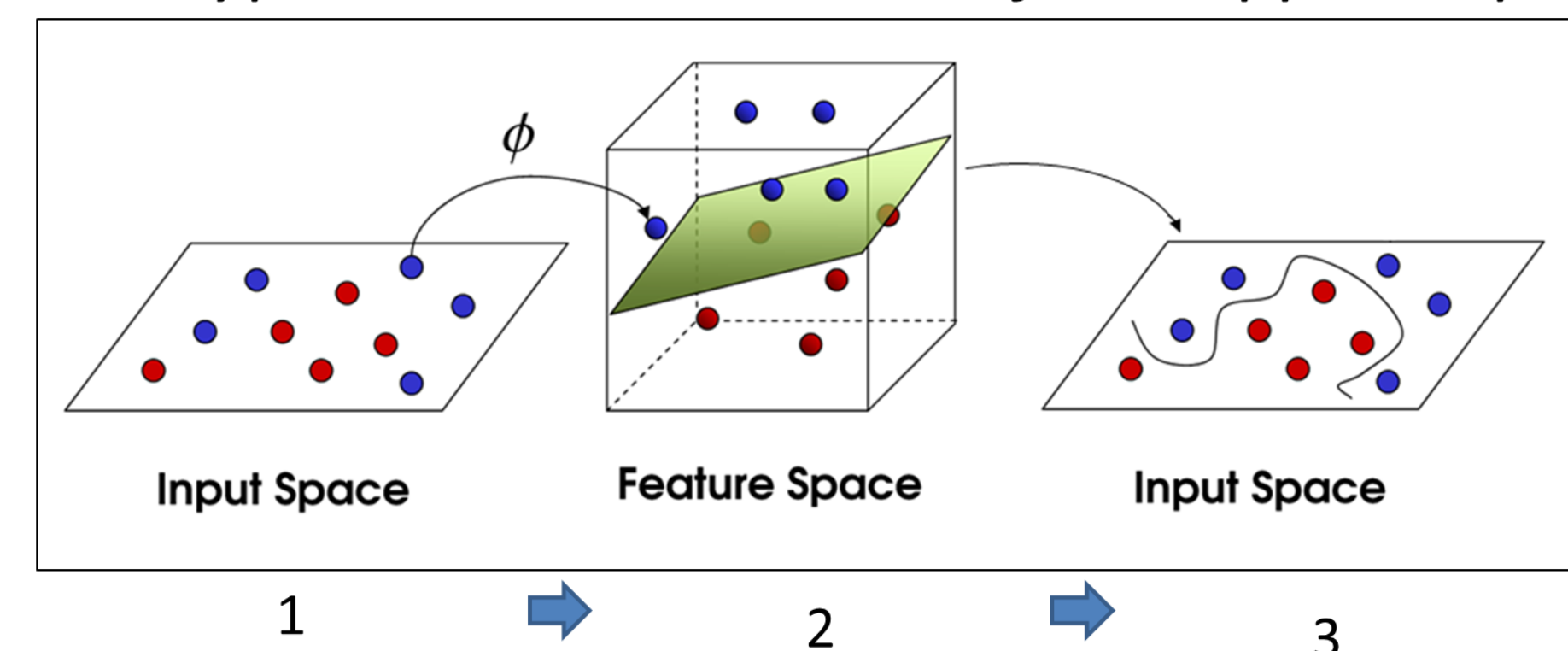


*Scholarpedia Function of Hippocampal subregions

Pattern Separation



We hypothesize that the role of the hippocampus in information processing is:



- 1) to restructure and refine the multimodal associative encoding provided by the entorhinal cortex (EC)
- 2) through a high dimensional adaptive transformation in dentate gyrus (DG)
- 3) and subsequent compressive encoding by the CA3

Analysis Methods

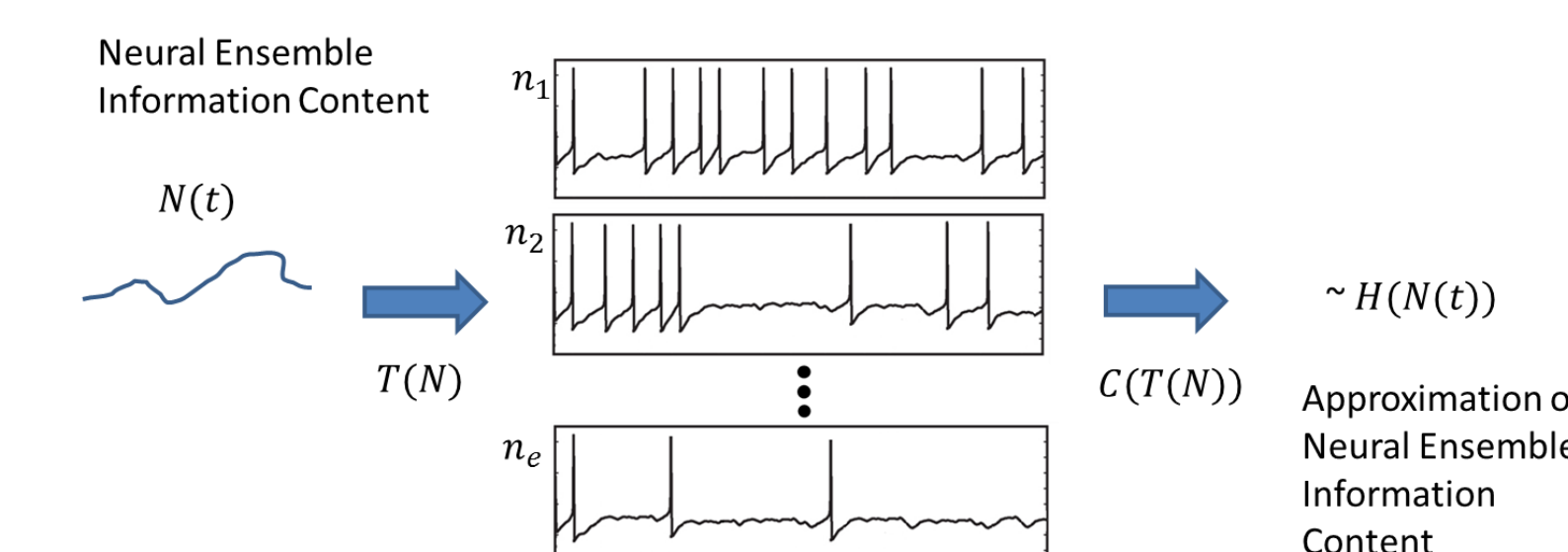
- Information theory provides entropy of a discrete random variable as a quantitative measure of information

$$H(X) = \sum_{x \in X} p(x) \log\left(\frac{1}{p(x)}\right)$$

- Can be applied to neuroscience to quantitatively measure the information content of firing neurons
- And it has been with various methods such as (not a complete list):

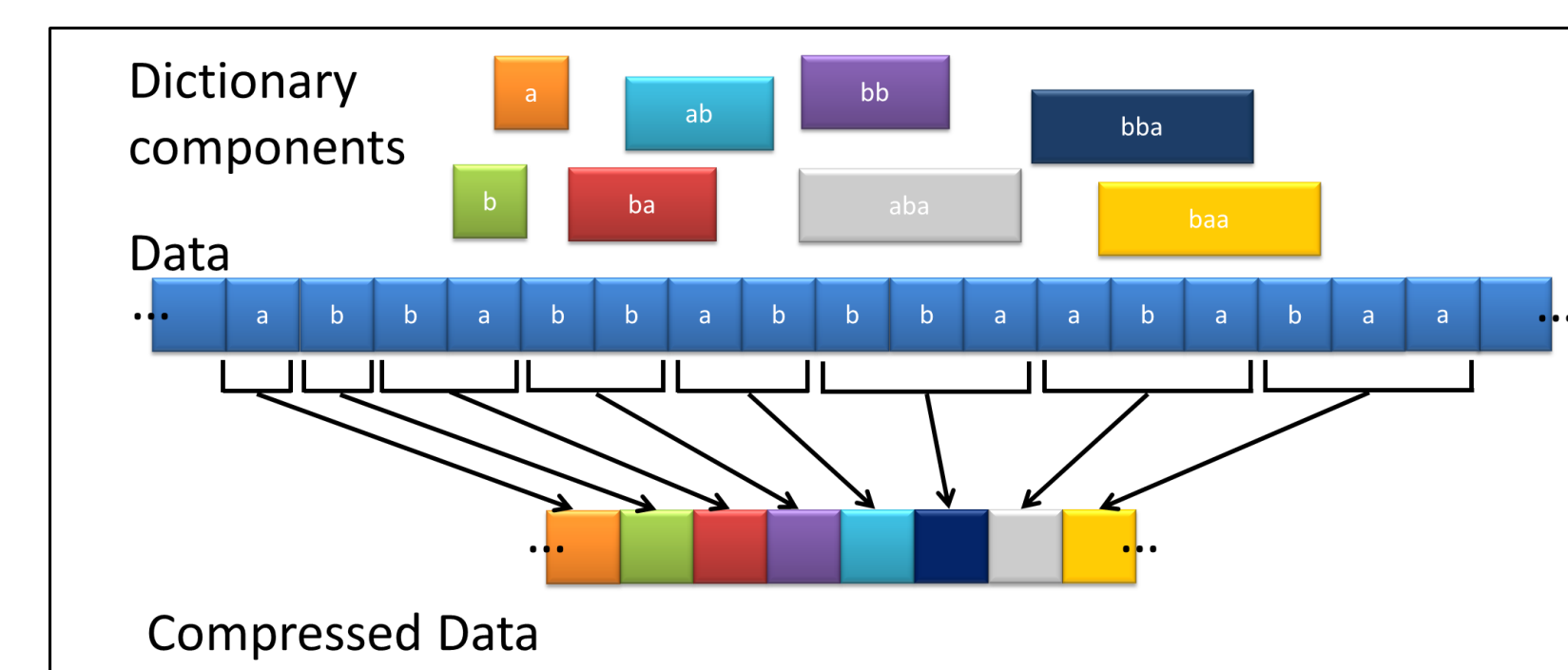
- Plug-in Entropy
- Jackknife debiased
- Asymptotically debiased
- Ma bound
- Bayesian/Dirichlet prior
- Coverage-adjusted
- Best upper bound

- But there are issues...
 - Entropy (and many other concepts from information theory) calculations require knowledge of the firing behavior probability distributions for the neurons - however
 - Limitations to in vivo recording capabilities
 - Neurons are somewhat deterministic
 - Neural plasticity effectively creates non-static distributions
 - Applied to single neurons but not ensembles

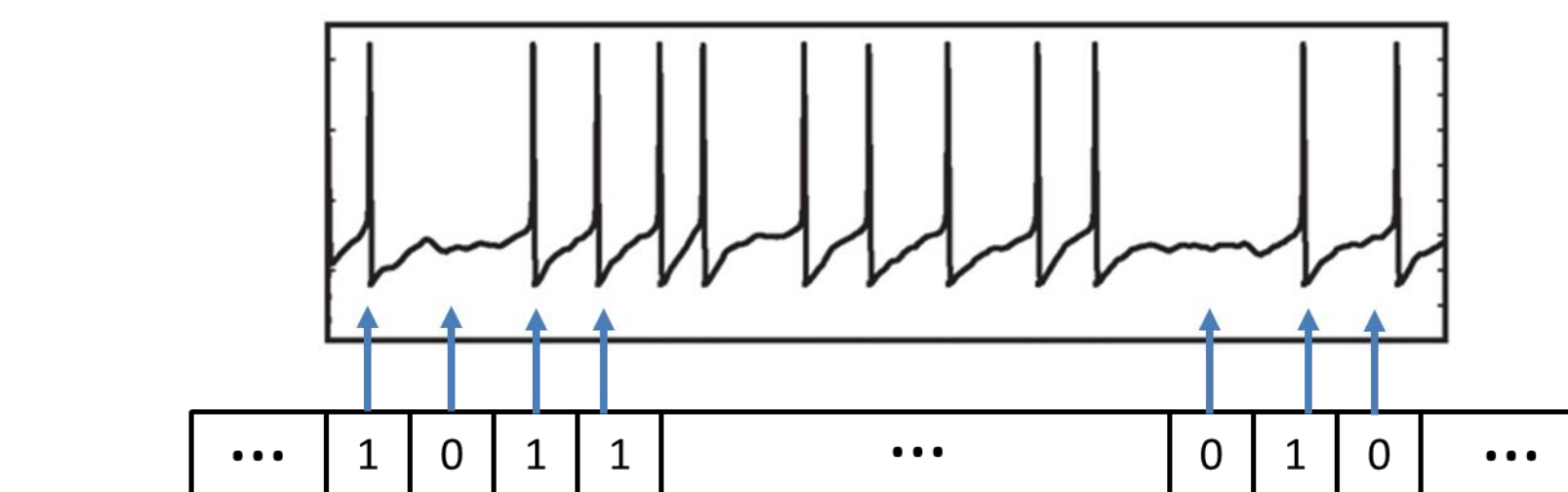


Compression

- Use complexity as a measure of compressibility in order to estimate entropy to quantitatively assess the information content of a signal
- Szczepanski et al. applied the general Lempel-Ziv complexity (LZ-Complexity) measure to estimate entropy of real and simulated neurons
- LZ Compression is a dictionary technique that does not require a probabilistic model
 - Rather dictionary compression techniques exploit redundancies in the data
 - LZ compression has been used in applications such as UNIX compress command and GIF compression



- LZ-Complexity is based upon measuring the rate of generation of new patterns along a sequence of characters in a string being compressed
- Applied to neuron spike trains, this technique looks for repeated spiking behavior over time

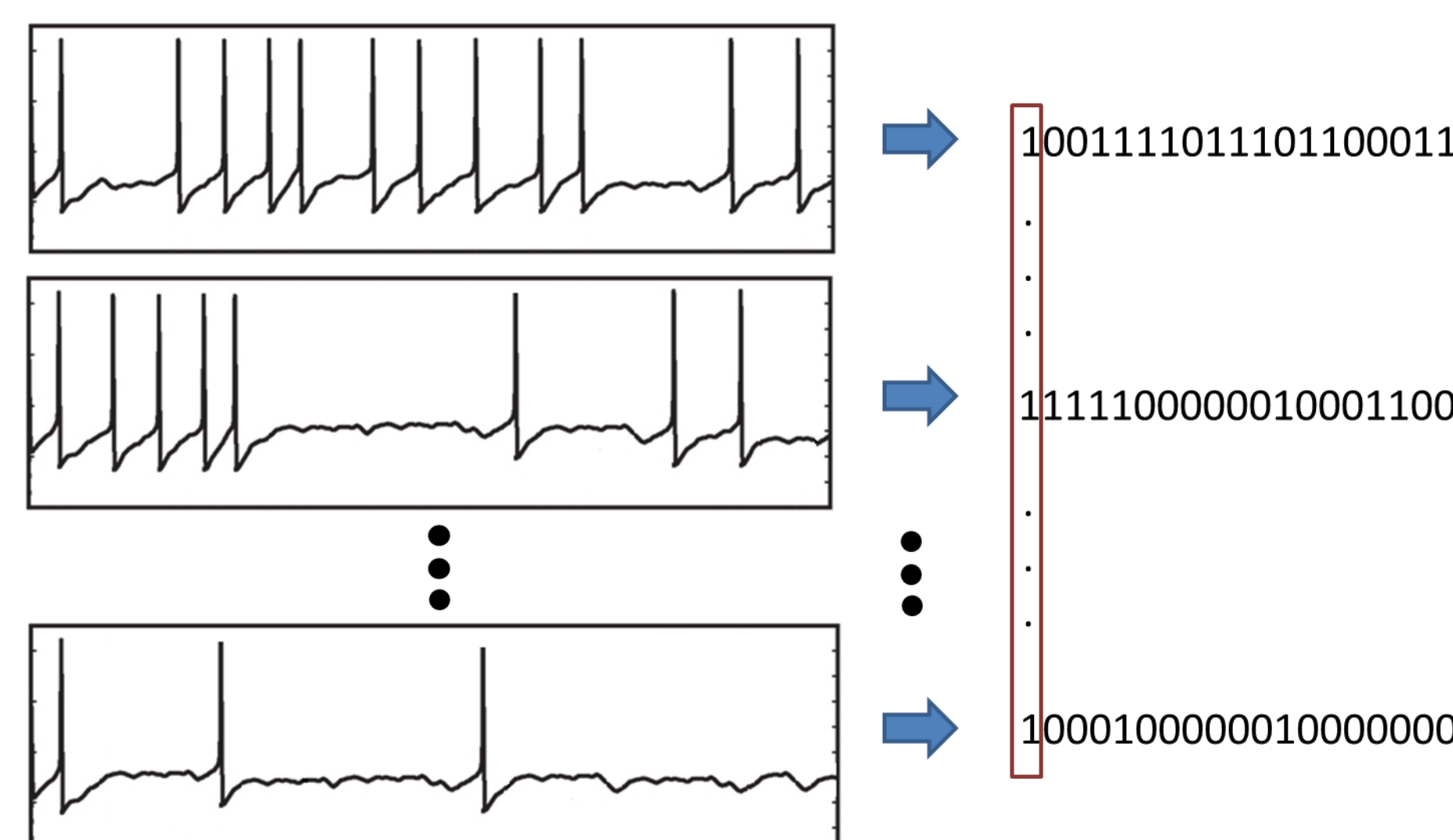


- Once the spike signal is converted into a binary signal, where an action potential is encoded as a one and the absence of activity by a zero, the normalized complexity may then be computed as follows:

$$c_{\alpha}(x^n) = \frac{C_{\alpha}(x^n)}{n} * \log_{\alpha} n$$

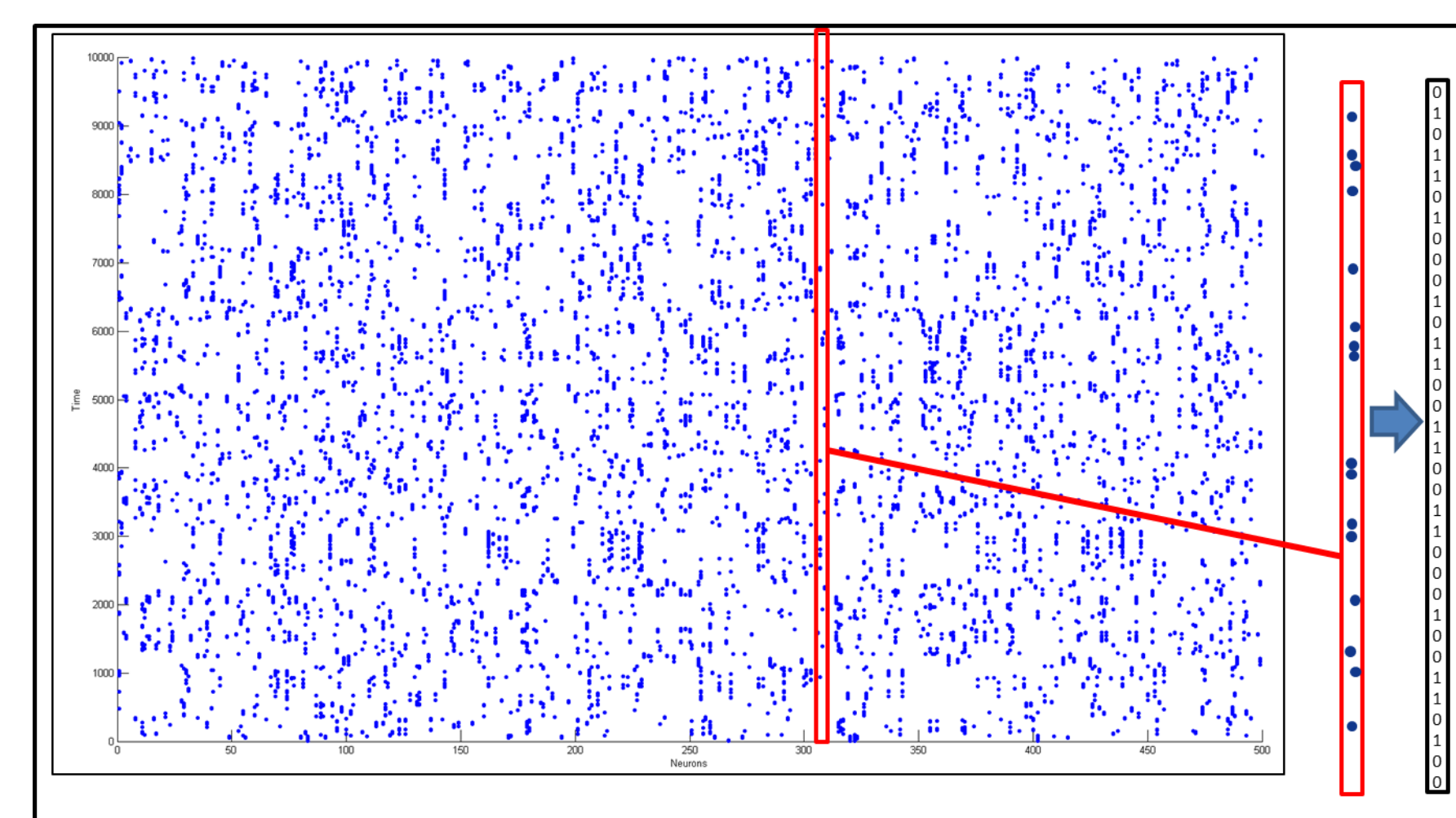
- Normalized complexity measures the generation rate of new patterns along a word of length n with letters from an alphabet of size α (in this case two)

- But unlike the work of Szczepanski et al., rather than applying LZ-Complexity analysis to individual neuron spike trains, we have applied the approach to a neural population as a whole
- Instead, by applying it across an entire neural ensemble, we assessed repeated patterns of neural co-activity



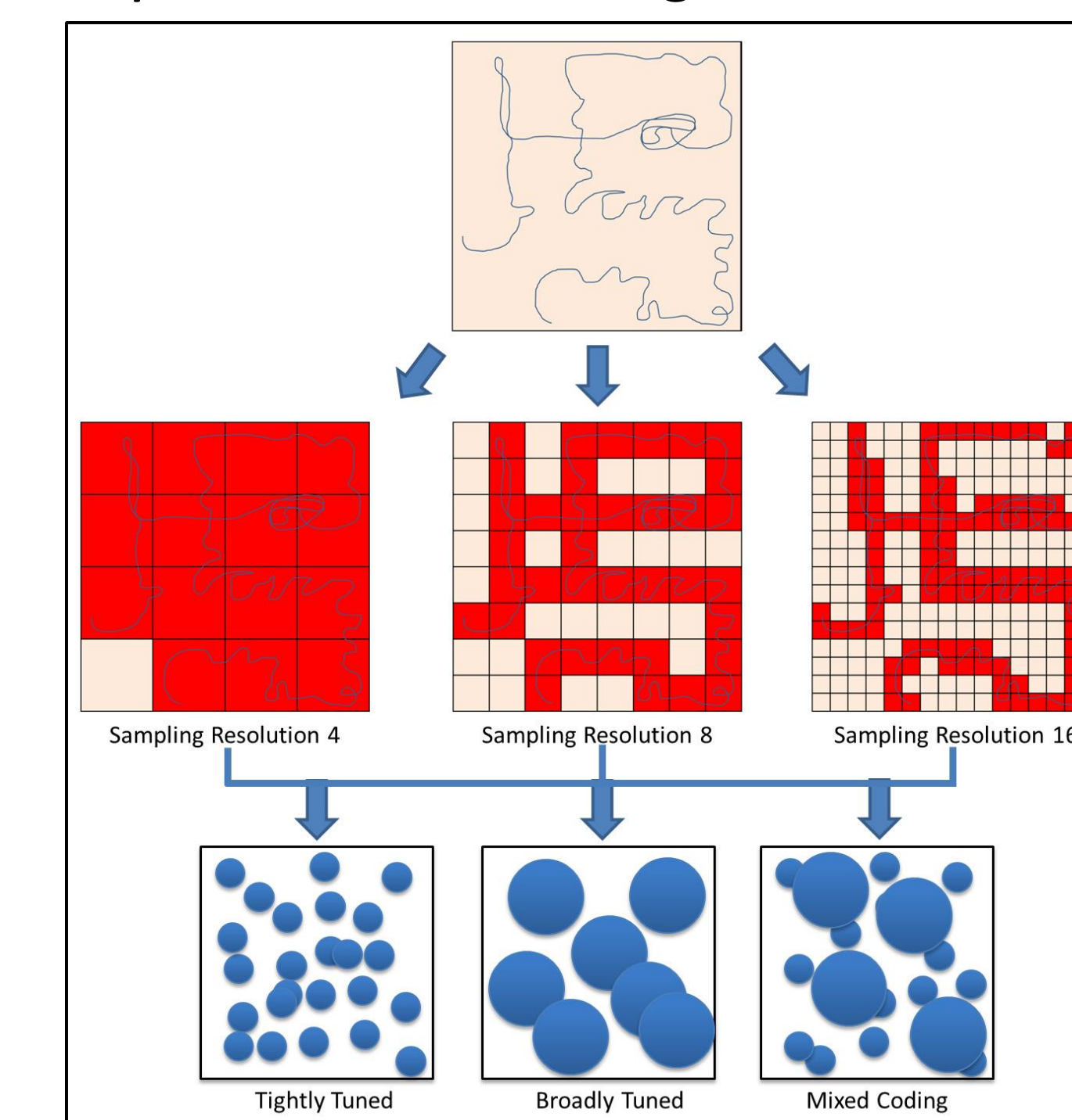
- It can be proven that as the string length (our series of neural firings in this case) goes to infinity, the supremum of the normalized complexity approaches the entropy of the signal S:

$$\lim_{n \rightarrow \infty} \sup c_{\alpha}(x^n) \leq H_{\alpha}(S)$$

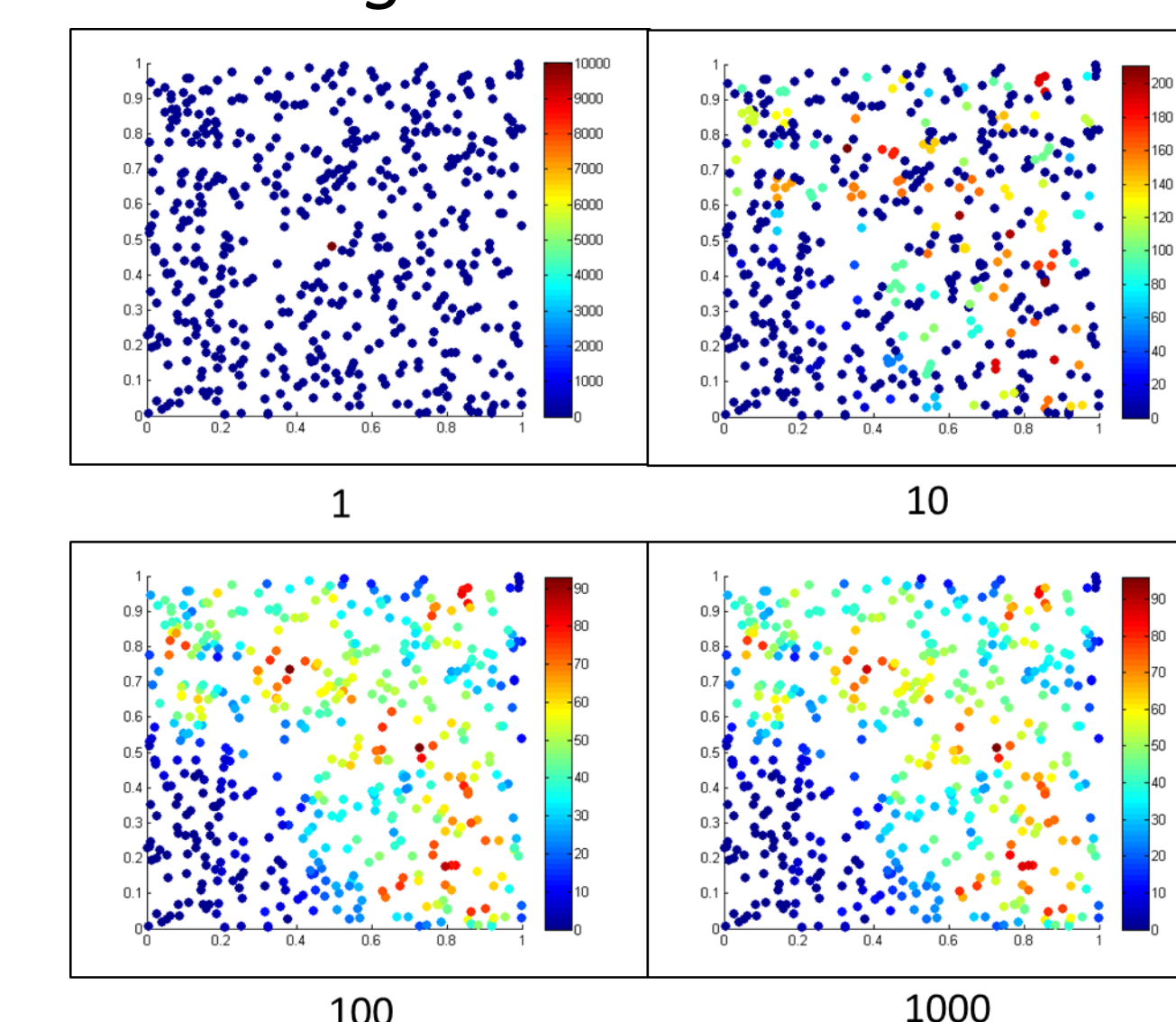


Results

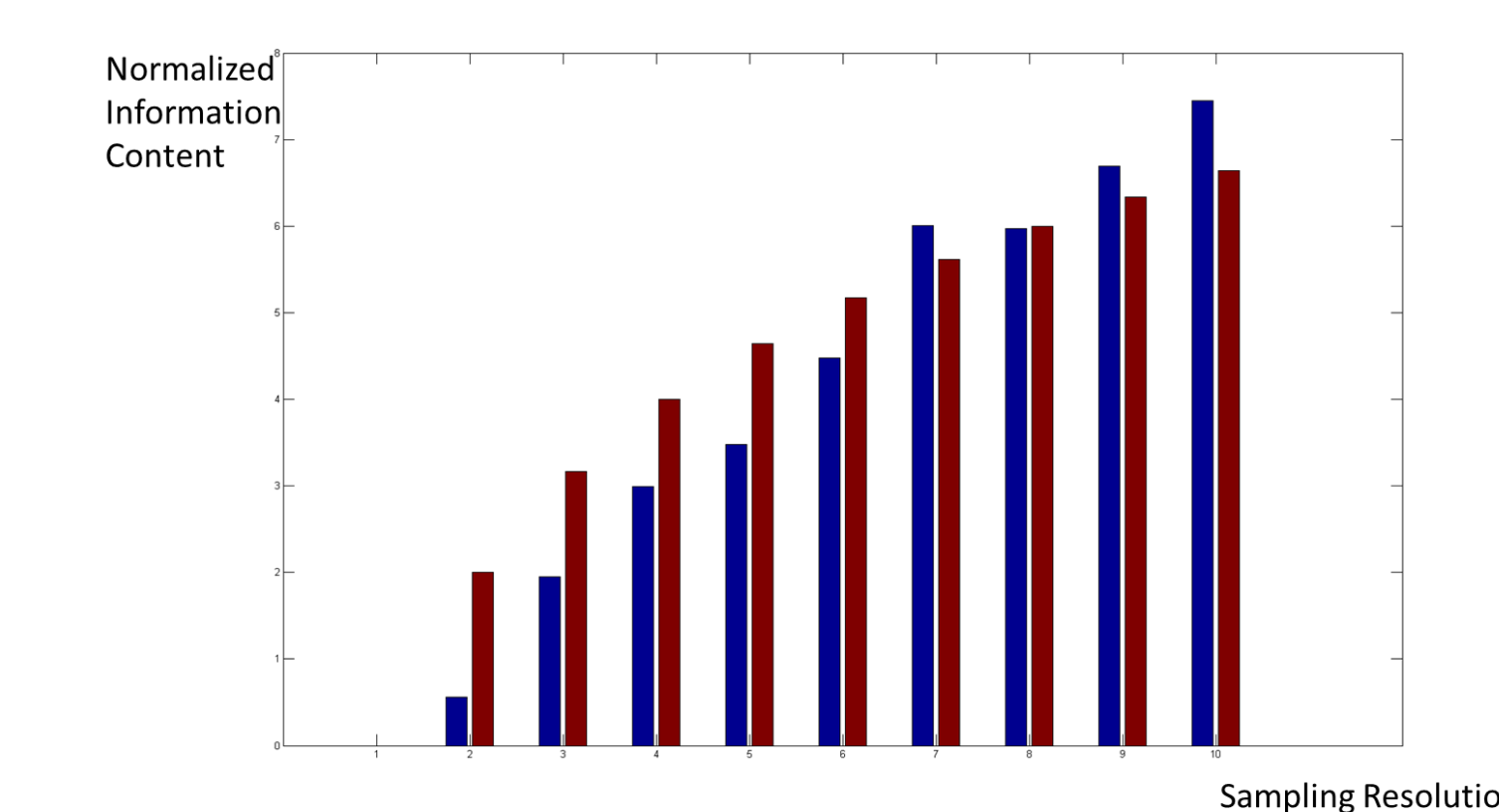
Computational Paradigms



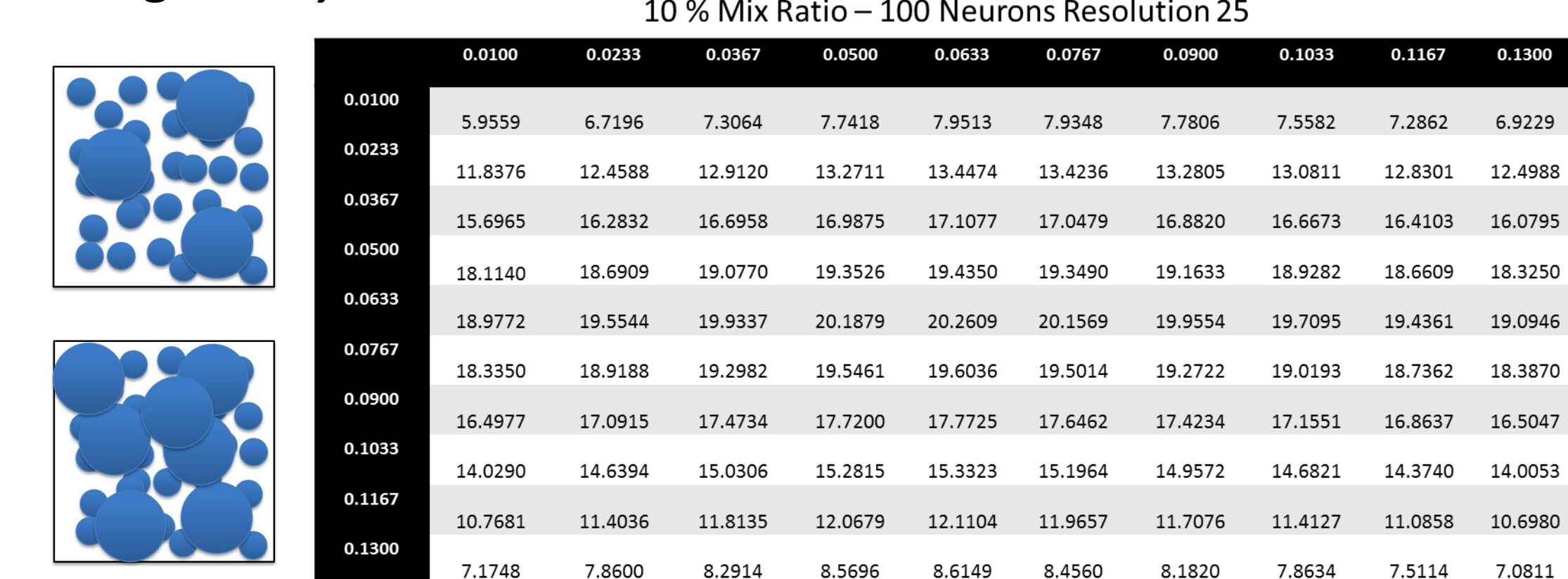
Neural Firing Across Resolutions



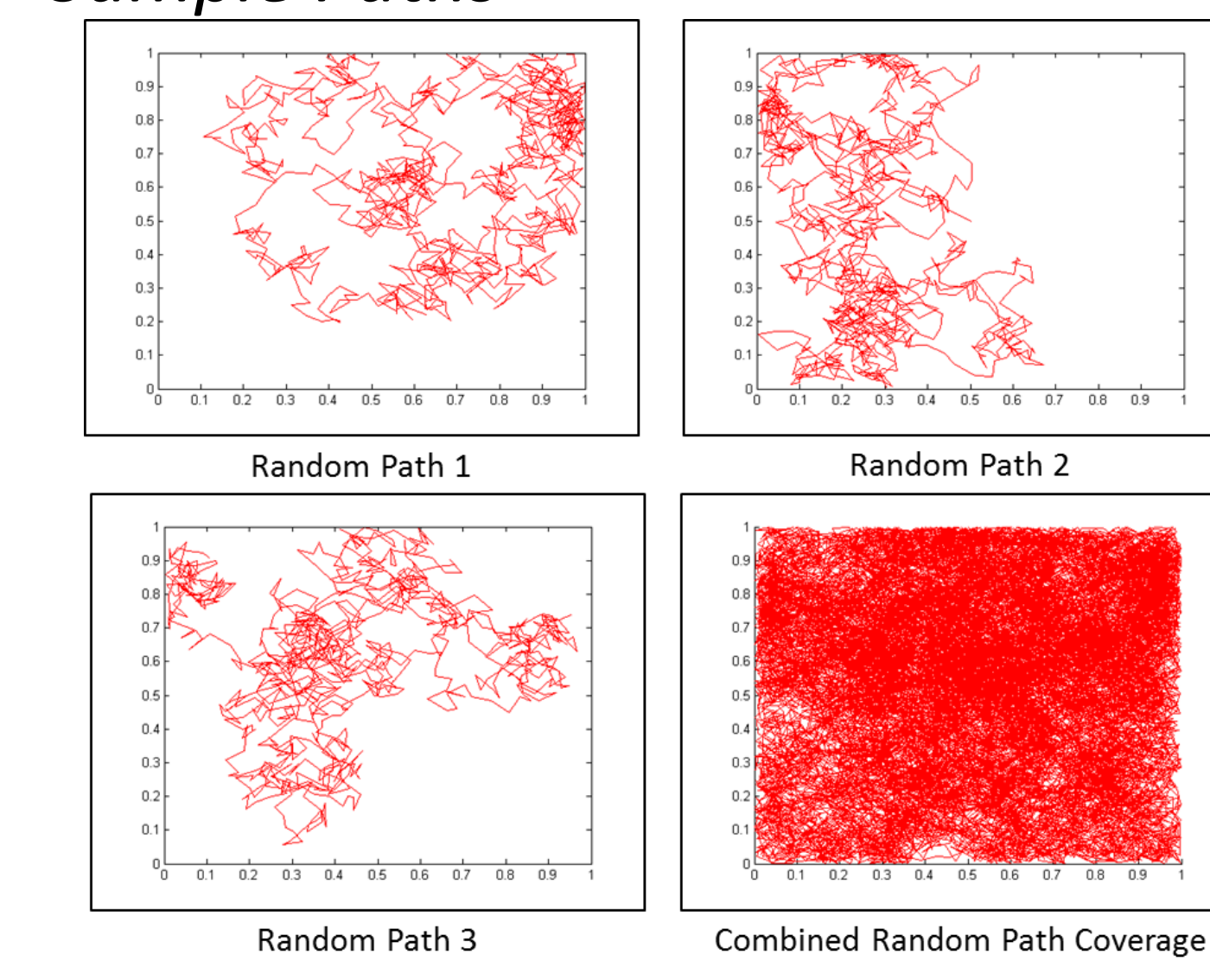
Resolutions 1-10



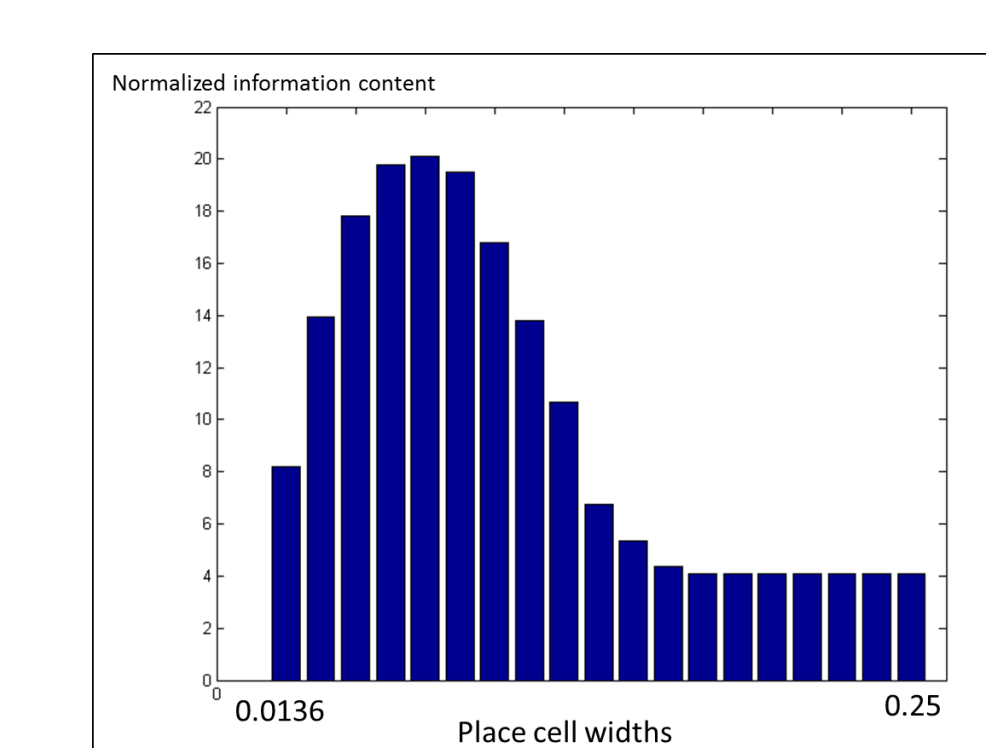
Mixed Coding Analysis



Sample Paths



Exploring Place Cell Widths



Summary

- Present a metric & computational paradigm for quantifying neural information content
 - Case study - used this framework to study the impact of hippocampal neurogenesis
 - Experimentally shown benefit to mixed coding**
 - Next investigate impact on CA3 network
- Present an alternative perspective on hippocampal function in information encoding & transformation
 - Implications for machine learning
 - Insights for neural computation