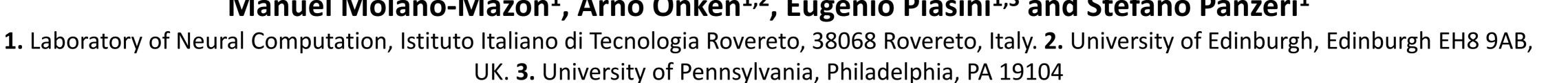


Synthesizing realistic neural population activity patterns using Generative Adversarial Networks

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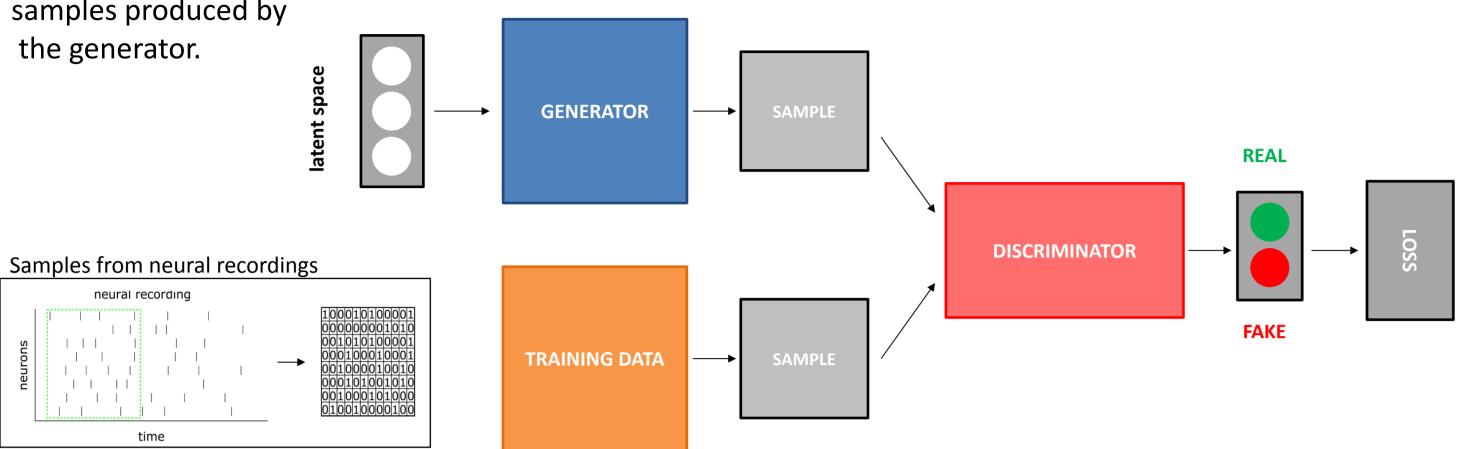
lag cov real

Summary

- We use GANs to simulate the concerted activity of a population of neurons.
- Spike-GAN generates spike trains that match the first- and second-order **statistics** of populations of tens of neurons.
- We apply Spike-GAN to a real dataset recorded from salamander retina and showed that it performs as well as state-of-the-art approaches.
- We exploit a trained Spike-GAN to construct importance maps to detect the most relevant statistical structures present in a spike train.

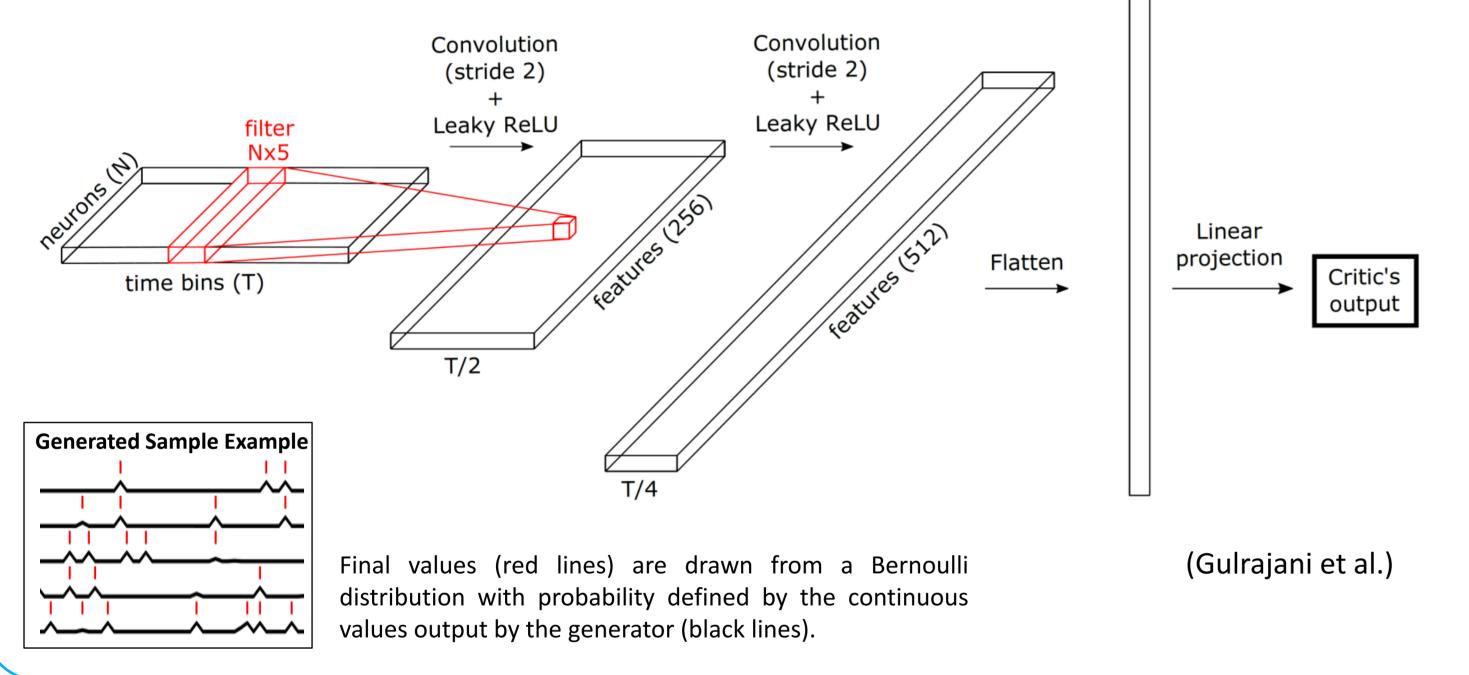
Generative Adversarial Networks

Generative Adversarial Networks (GANs) (Goodfellow et al.) are based on the competition between two deep neural networks: the generator tries to produce samples that are indistinguishable from the ones contained in a given training dataset; the discriminator aims at distinguishing between samples from the training dataset and samples produced by



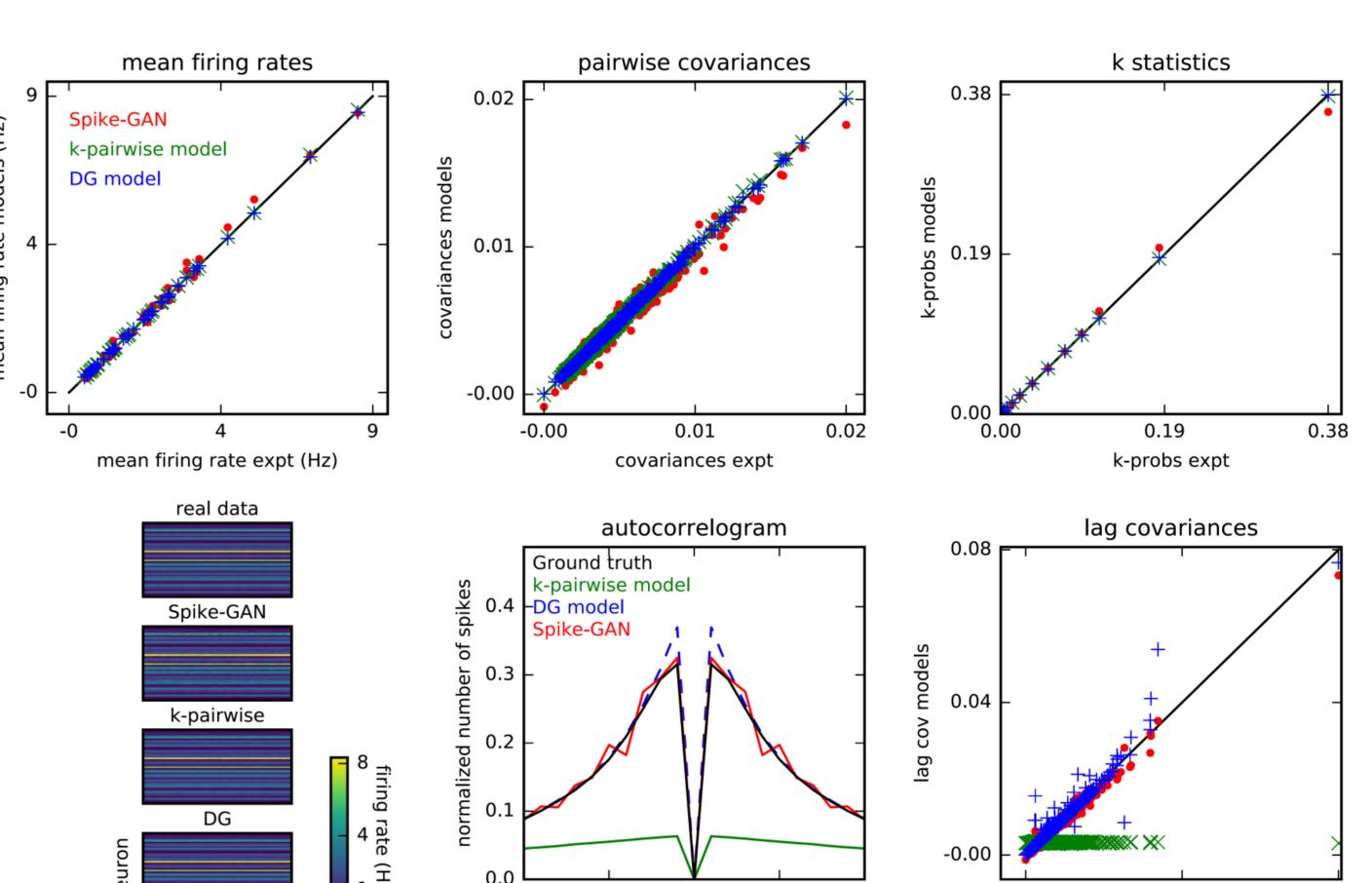
Spike-GAN

Spike-GAN adapts the Wasserstein-GAN variant described by Arjovsky et al.. Samples are transposed so as to input the neurons' activities into different channels. The convolutional filters (red box) span thus all neurons but share weights across the time dimension. The architecture of the generator is the same as that of the critic, used in the opposite direction and with sigmoid units in the last layer.



Fitting neural data from salamander retina

We tested Spike-GAN on recordings coming from the retinal ganglion cells of the salamander retina (Marre et al.). Spike-GAN performs as well as state-of-the-art approaches based on the maximum entropy (Tkacik et al.) and the dichotomized Gaussian (Lyamzin et al.) frameworks.



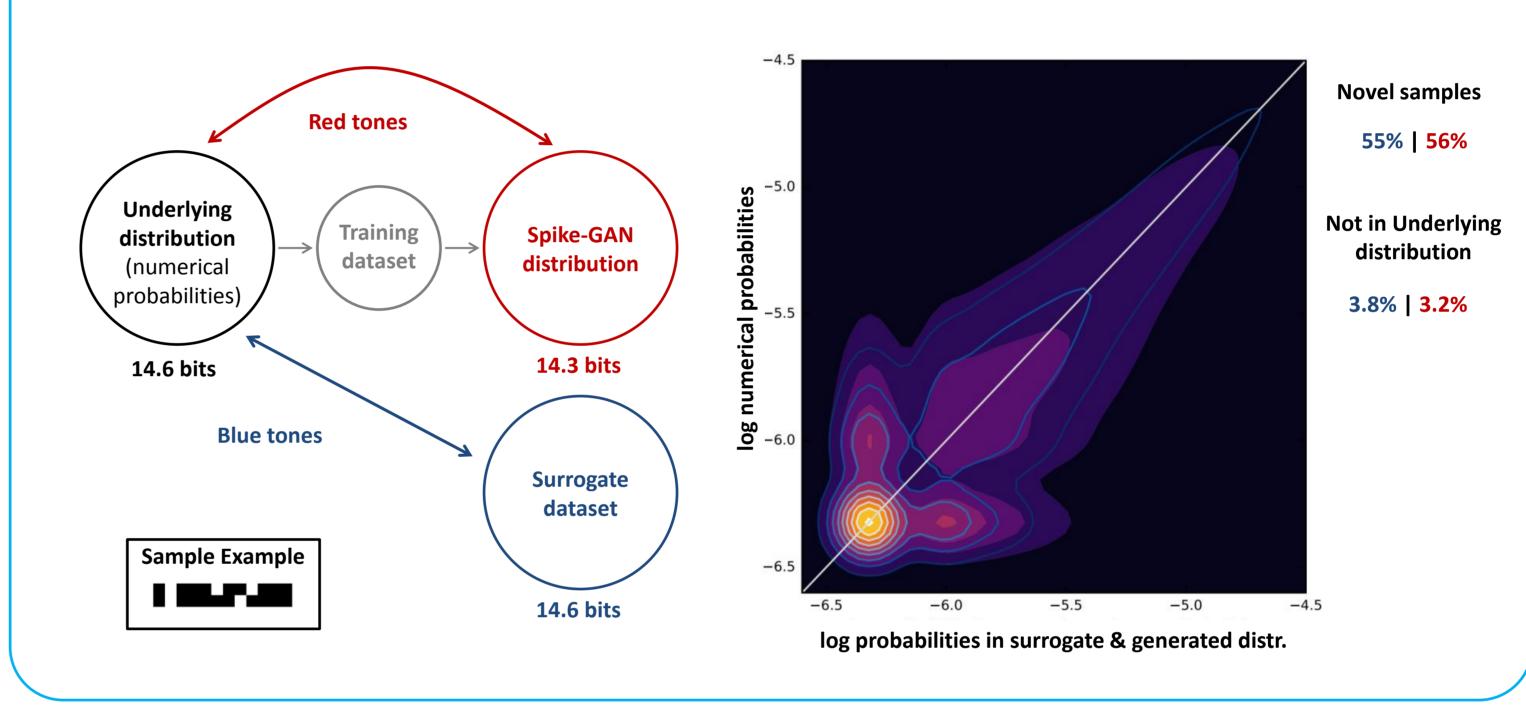
Fitting the whole probability distribution

time

We simulated activity patterns for a small 'population' of 2 neurons during 12 ms and evaluated how well Spike-GAN fits the whole probability density function from which the patterns are drawn.

time (ms)

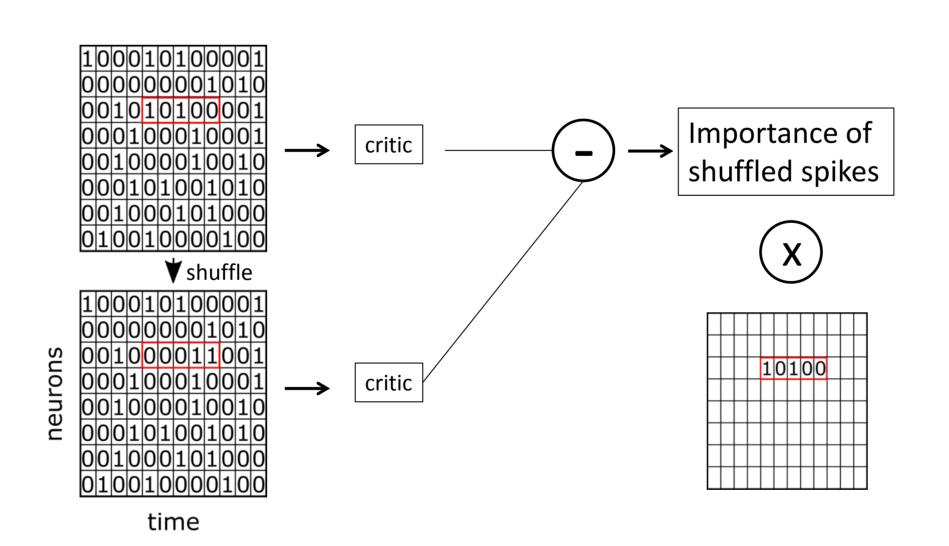
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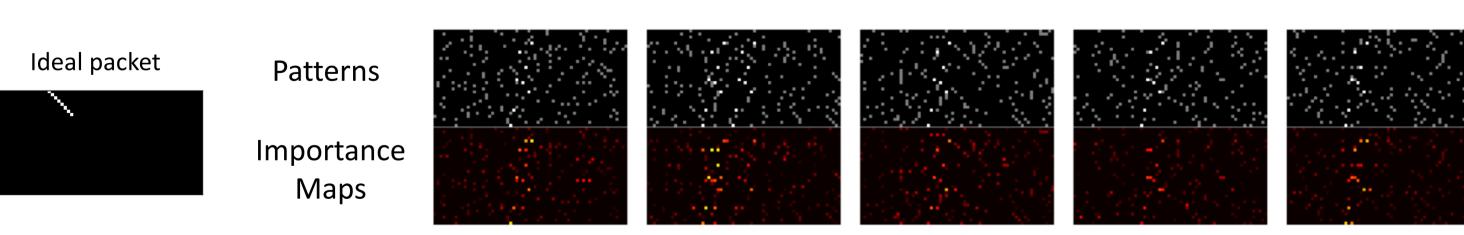


Finding relevant patterns of neural activity

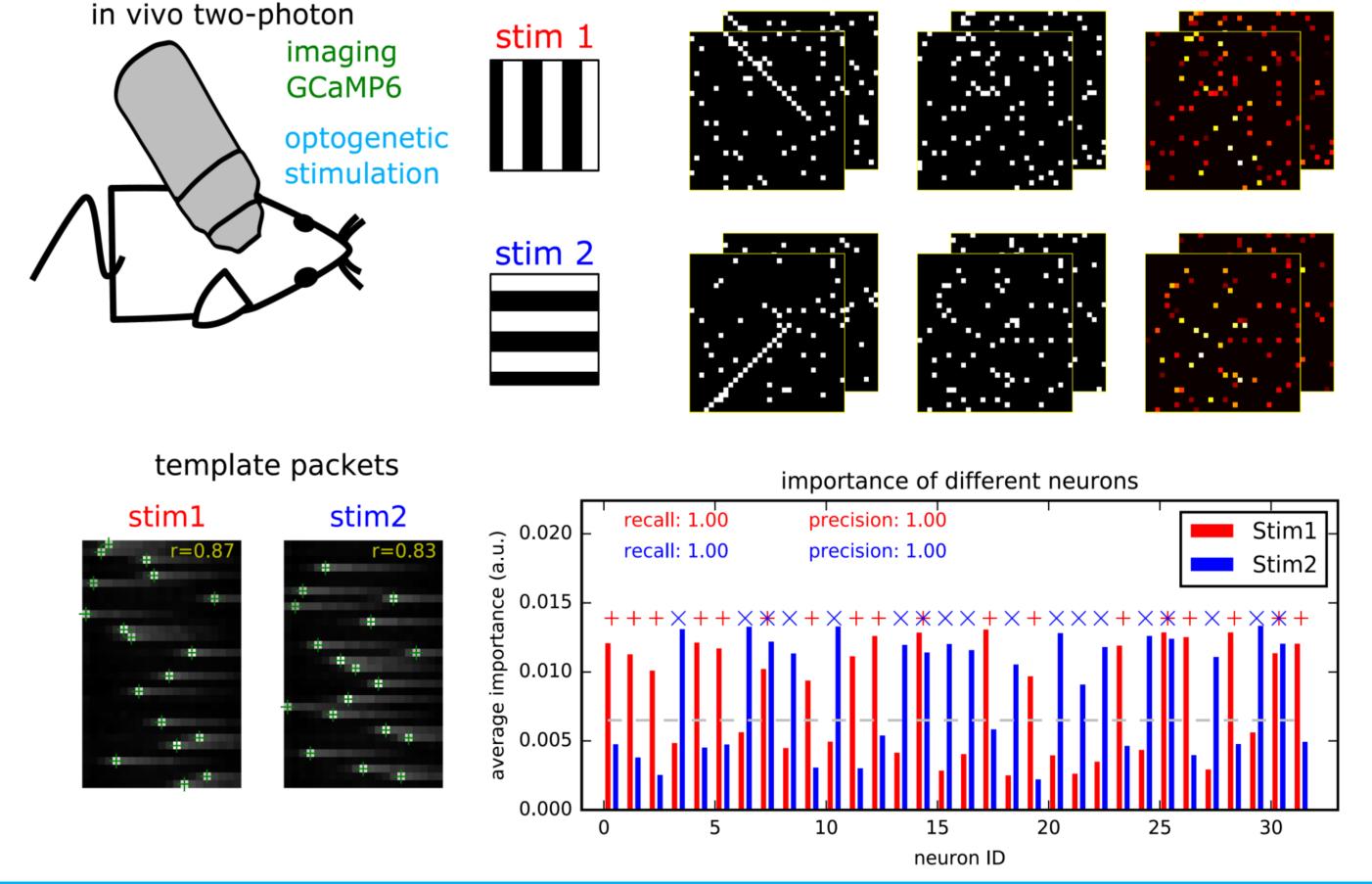
Importance maps: We infer the most relevant features characterizing a given neural activity pattern by enquiring a trained critic:

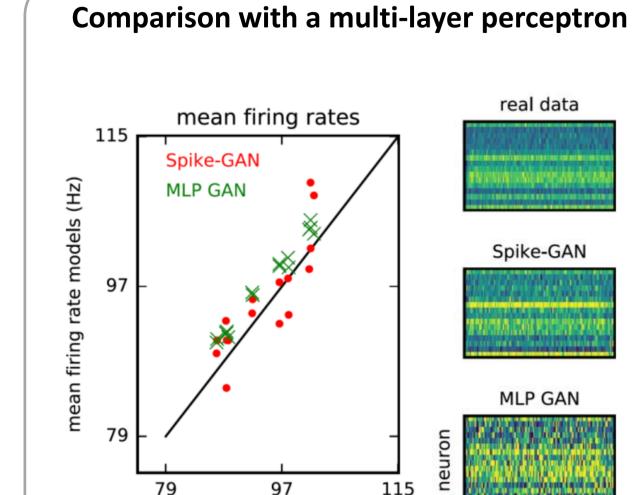
- 1. Compute the output produced by the critic for that particular pattern.
- 2. Shuffle across time the spikes emitted by a **neuron** during a specific period of time and compute again the output of the critic.
- 3. The absolute difference between the two outputs gives the importance of shuffled spikes.
- 4. Multiply the masked original sample by the importance.
- 5. Sum up all resulting maps for all neurons and time periods to get the importance map.

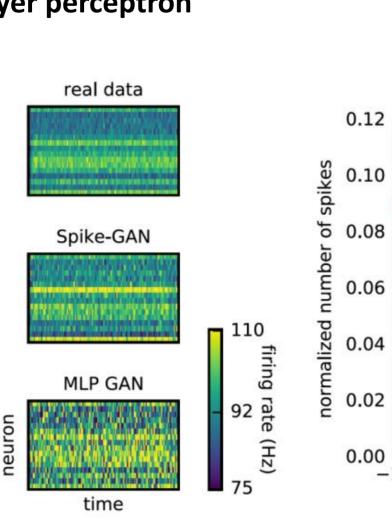


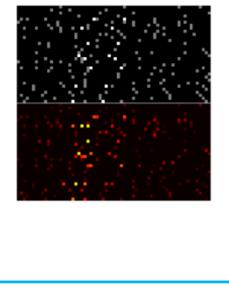


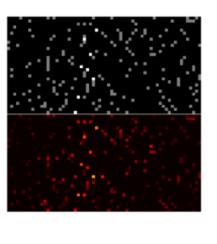
Hypothetical experiment: N repetitions of a behavioral task, where a mouse has to discriminate two different stimuli (vertical/horizontal stripes). By means of two-photon calcium imaging the activity of a population of V1 neurons in the visual cortex of the mouse is recorded in response to the two stimuli.





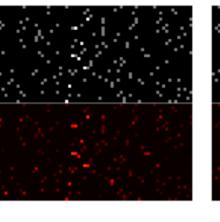


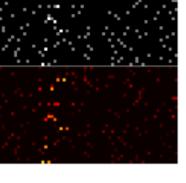




autocorrelogram

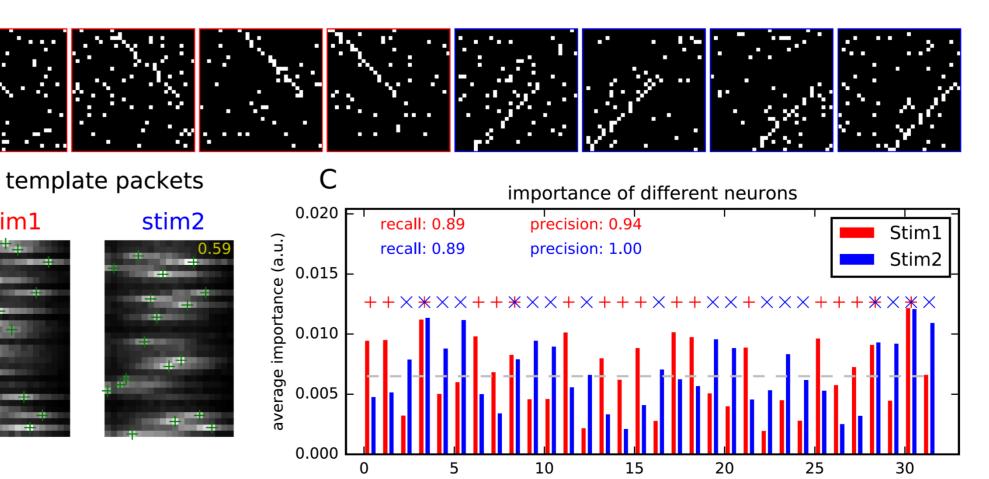
time (ms)





lag covariances 0.00

Less reliable packets



neuron ID

Different number of samples

Code

https://github.com/manuelmolano/Spike-GAN

mean firing rate expt (Hz)

References

1. Arjovsky et al. arXiv 2017. 2. Goodfellow et al. NIPS 2014. 3. Gulrajani et al. NIPS 2017. 4. Odena et al. Distill 2016. 5. Marre et al. IST Austria 2014. 6. Tkacik et al. Plos Comp. Biol. 2014. 7. Lyamzin et al. Front. Comp. Neurosci. 2010.

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lag cov real

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false positive rate