are generated by multiple thalamic inputs that have temporally different responses to the stimulus (Fig. 1). Thalamic inputs that respond slowly to visual stimuli generate slow responses in cortical regions, whereas those responding faster generate fast responses.

Lien and Scanziani's results, taken together with previous work[3–10], raise the interesting possibility that cortical direction selectivity is generated through a common mechanism — the convergence of temporally diverse thalamic inputs — in rodents, cats and primates. But as with all research, some questions remain open.

For instance, the authors focus their study on the middle layers of the visual cortex, which receive the bulk of the thalamic input[11]. As Lien and Scanziani show, many thalamic inputs in these middle cortical layers are not direction selective, but their combined activity is. It remains unclear whether thalamic inputs that target other cortical layers (or serve other functions) can encode direction selectivity through different mechanisms. For example, neurons in the superficial layers of the cortex might derive their direction selectivity from thalamic neurons that are themselves direction selective[12].

It is also known that thalamic inputs to the visual cortex are arranged by their receptive-field position — inputs that have receptive fields close to one another in the field of view are clustered together. However, it is not yet known whether the thalamic inputs are also arranged according to their temporal properties. If so, this could explain why spatial position and direction preference tend to change together in different

neurons across the visual–cortical map[13]. Whatever the answers are, it is becoming increasingly clear that the visual cortex gen-erates stimulus selectivity, such as prefer-ences for direction and orientation, through thalamo–cortical convergence. Lien and Scanziani's work shows that this mechanism is better preserved across mammals than was previously thought. ∎

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Two artificial synapses are better than one

Emerging nanoelectronic devices could revolutionize artificial neural networks, but their hardware implementations lag behind those of their software counterparts. An approach has been developed that tips the scales in their favour. SEE ARTICLE P.60

GINA C. ADAM

Inspired by the brain's neural networks, scientists have for decades tried to construct electronic circuits that can process large amounts of data. However, it has been difficult to achieve energy-efficient implementations of artificial neurons and synapses (connections between neurons). On page 60, Ambrogio *et al.*[1] report an arti-ficial neural network containing more than 200,000 synapses that can classify complex collections of images. The authors' work dem-onstrates that hardware-based neural networks that use emerging nanoelectronic devices

can perform as well as can software-based networks running on ordinary computers, while consuming much less power.

Artificial neural networks are not programmed in the same way as conventional computers. Just as humans learn from experience, these networks acquire their functions from data obtained during a training process. Image classification, which involves learning and memory, requires thousands of artificial synapses. The states (electrical properties) of these synapses need to be programmed quickly and then retained for future network operation.

Nanoscale synaptic devices that have programmable electrical resistance, such