Neuromorphic computing at scale

The paper *"Neuromorphic Computing at Scale"*, published in *Nature* in 2025, explains the current progress and future goals of neuromorphic computing. Neuromorphic computing is a way of building computer systems that work more like the human brain. These systems are designed to be very energy-efficient, fast, and able to learn over time. While there are already some neuromorphic chips available—like Loihi from Intel or BrainScaleS—they haven't yet shown any big breakthrough applications. The authors say the field is waiting for a big moment, like when AlexNet made deep learning popular back in 2012.

The paper lists six important features that neuromorphic systems need to work well:

1. Event-driven computing, where the system only works when it needs to—just like how our brain only fires neurons when there's input.
2. Sparsity, which means not all parts are active at once, saving energy.
3. Hierarchical structure, which copies how the brain is built in layers and modules.
4. Local learning, where learning happens within each small part of the system instead of needing a big central processor.
5. Energy efficiency, to keep power use low.
6. Asynchronous communication, meaning the parts of the system work independently and don't need a shared clock.

The authors also talk about how neuromorphic computing is similar to deep learning in its early days. The hardware exists, but we don't yet have a big success story that shows how useful it can be. That's what they call the "AlexNet moment" for neuromorphic computing—one major success that convinces people it's the future. They believe this might happen in areas like robotics, smart sensors, or devices that learn on their own in the real world.

One of the big problems right now is the software. Different neuromorphic chips use different programming tools, which makes it hard to write programs that work on all of them. In traditional AI, we have easy-to-use tools like TensorFlow or PyTorch, but nothing like that exists yet for neuromorphic systems. The paper says we need better software tools, shared programming platforms, and ways to test and compare different systems.

The authors also point out that we can't use regular performance metrics (like accuracy or speed) to judge neuromorphic systems. Instead, we should look at things like how much energy they use per spike, how fast they respond in real time, and how well they learn over long periods. They recommend creating new benchmarks and tests that are more suited to neuromorphic computing.

Another exciting topic in the paper is the use of new memory devices like memristors and phase-change memory (PCM). These memory types can work like brain synapses and allow systems to do processing and memory storage in the same place. This could remove the slow "back-and-forth" between processor and memory that limits traditional computers.

In the end, the authors suggest that for neuromorphic computing to grow, we need a full-team effort—from chip designers and AI researchers to neuroscientists and software developers. They see this field as having a lot of promise, but it still needs the right tools, collaboration, and a big success story to move forward.