Depth-inverting autoencoders: a self-supervised testing ground for recurrent visual inference

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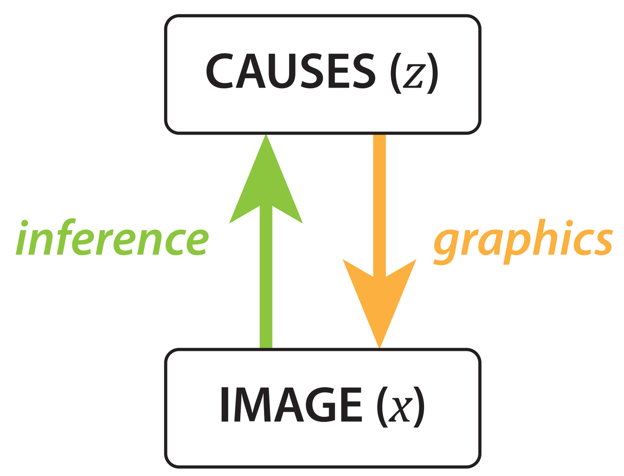
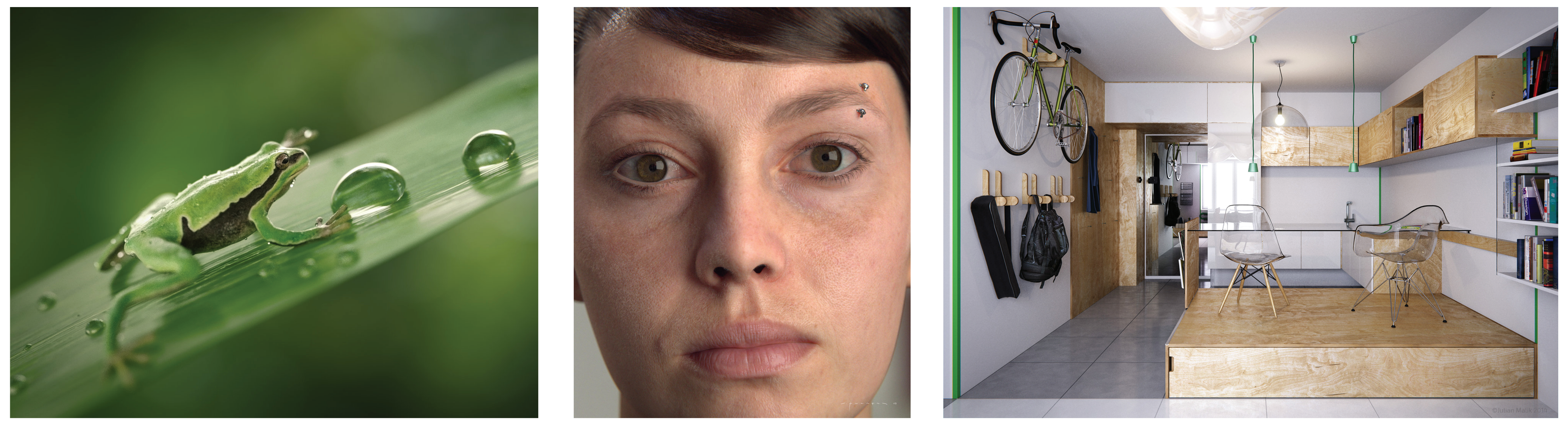
-BACKGROUND-

Visual **inference** aims to discover the **causes** that explain an image

This can be understood as a process of **inverse graphics**



Graphics is easy(-ish), **inference is hard**



Graphics is easy: these images were rendered in commercially available software (Blender)

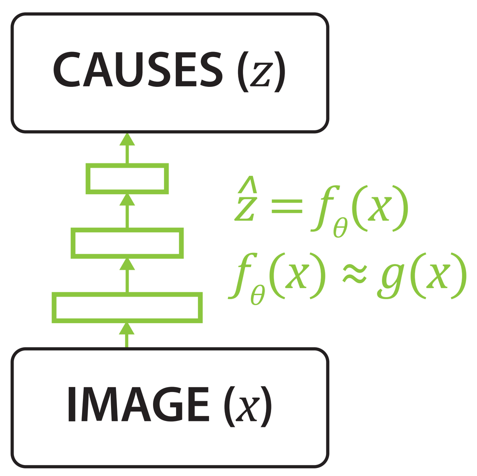
Can we leverage graphics for inference?

State-of-the-art computer vision models (**DNNs**) cannot do this as they are **feedforward**

Incorporating a graphics engine into neural networks requires **recurrent connections**

Recent evidence[1-3] suggests that adding **recurrent connections** can **improve** performance, especially on **challenging images**

FEEDFORWARD DNN



Visual cortex is also highly recurrent, and recurrent models better **predict brain data**[1,4-6]

GOAL: UNDERSTAND HOW RECURRENT PROCESSING ENABLES MORE ROBUST INFERENCE IN BRAINS AND MACHINES

-METHODS-

Use **simple images** of digits to foster understanding

Focus on **occlusions** as a drastic form of information loss that is challenging for inference

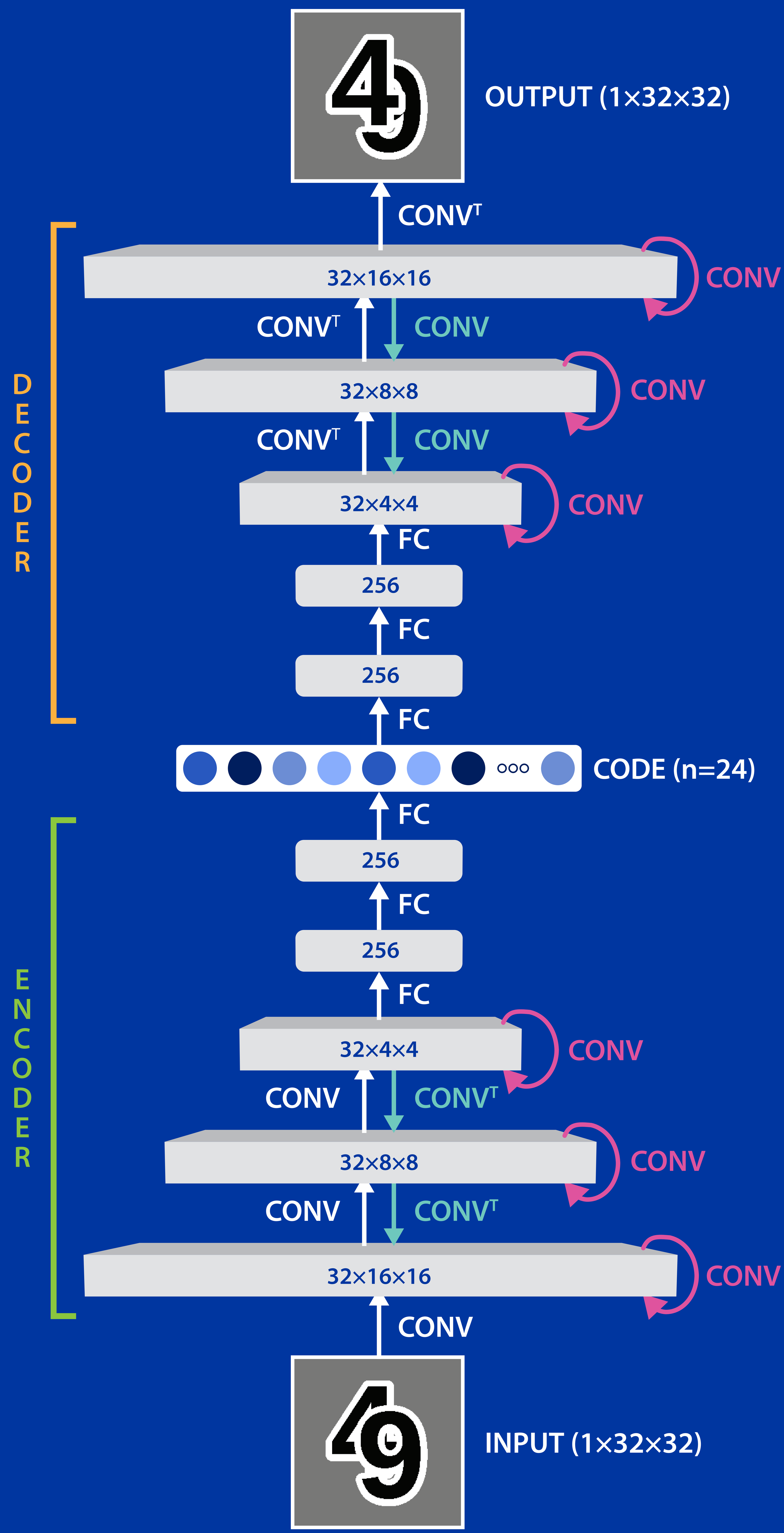
Use (deep convolutional) **autoencoders** to learn interesting representations and computations without supervision

Task: given an image of occluding digits, produce an image with the same digits in the **opposite depth order**

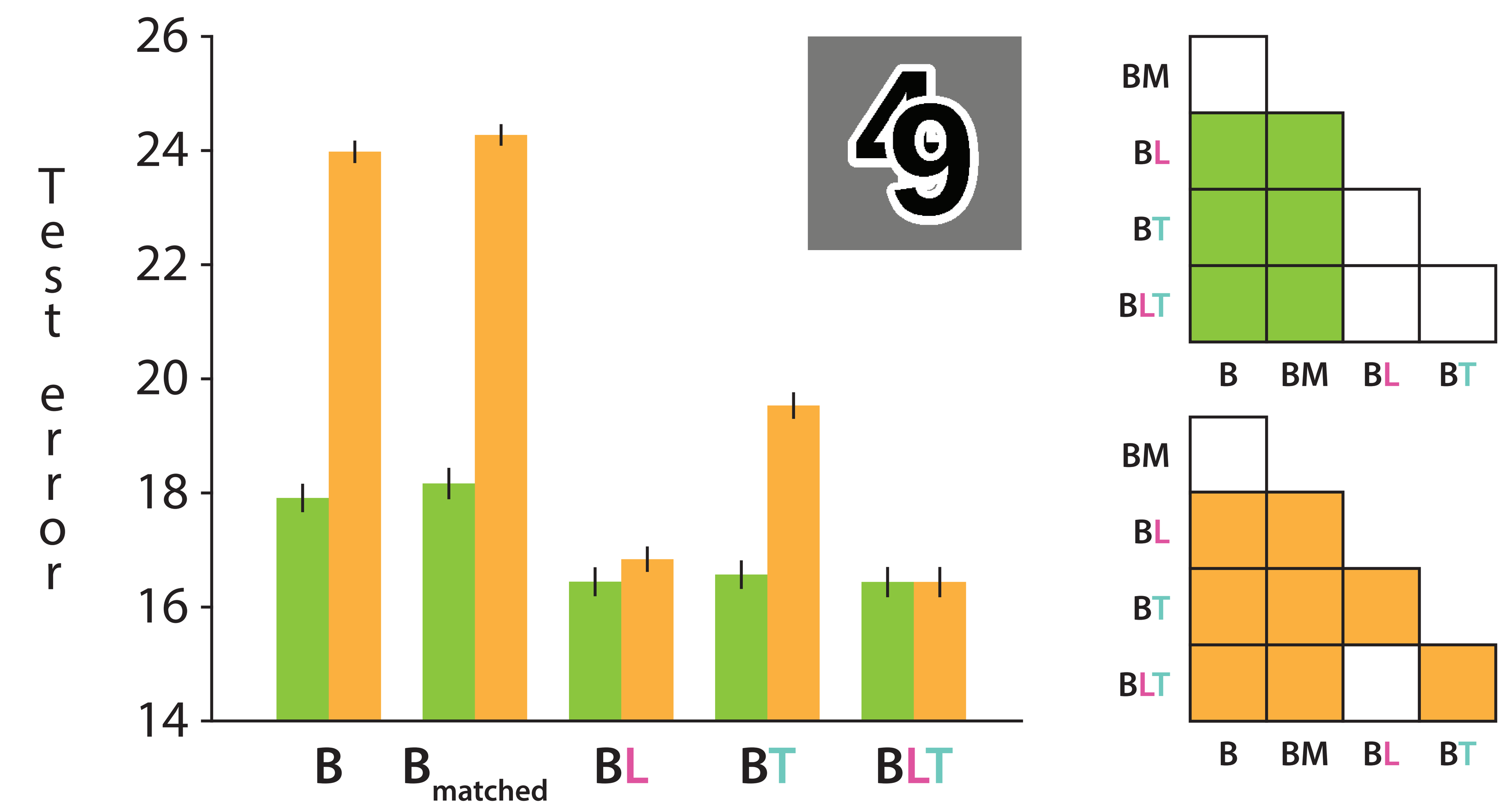
Train on 10,000 images with **random digits in random positions**

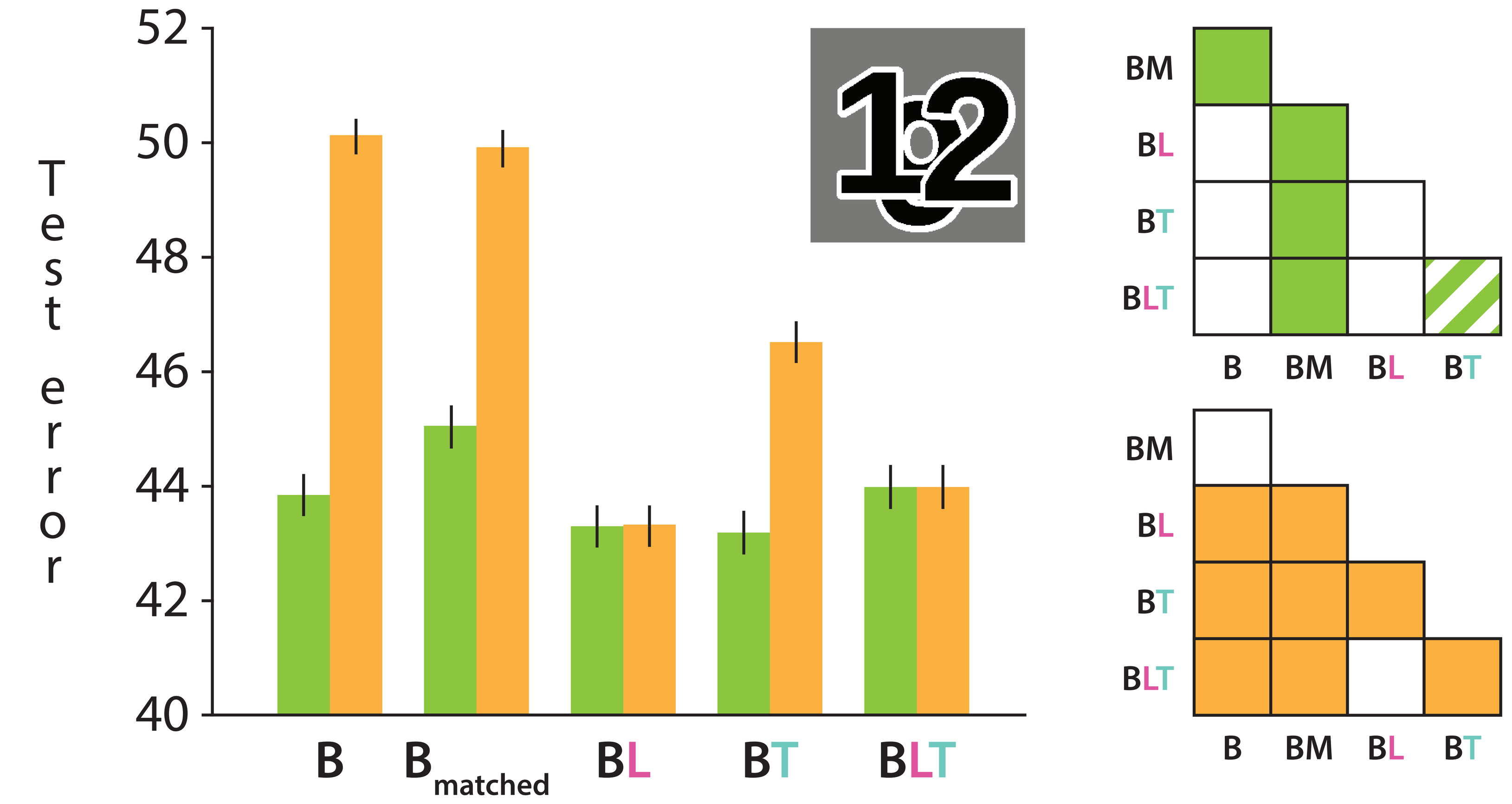
Test on 1,000 new images with pairs of digits **not seen during training**

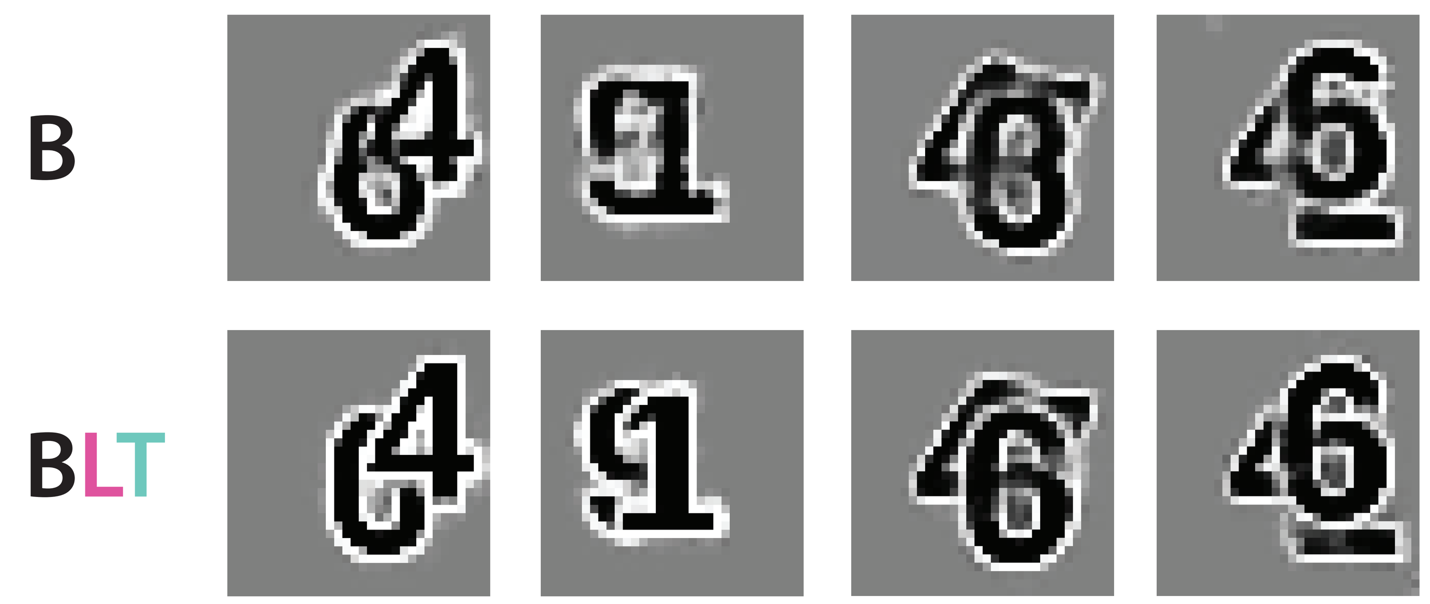
Compare results with various forms of recurrence



-RESULTS-







RECURRENCE HELPS, BUT:
(1) MOSTLY LATERAL CONNECTIONS
(2) MOSTLY DECODER
(3) MOSTLY SHARPENING?

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4. Kubilius, J. et al. Brain-Like Object Recognition with High-Performing Shallow Recurrent ANNs. 1–19 (2019).
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