Flexible Learning Reading Group @TU Berlin
2nd Session: 7th of August 2019

Task-Driven Convolutional Recurrent Models of the Visual System

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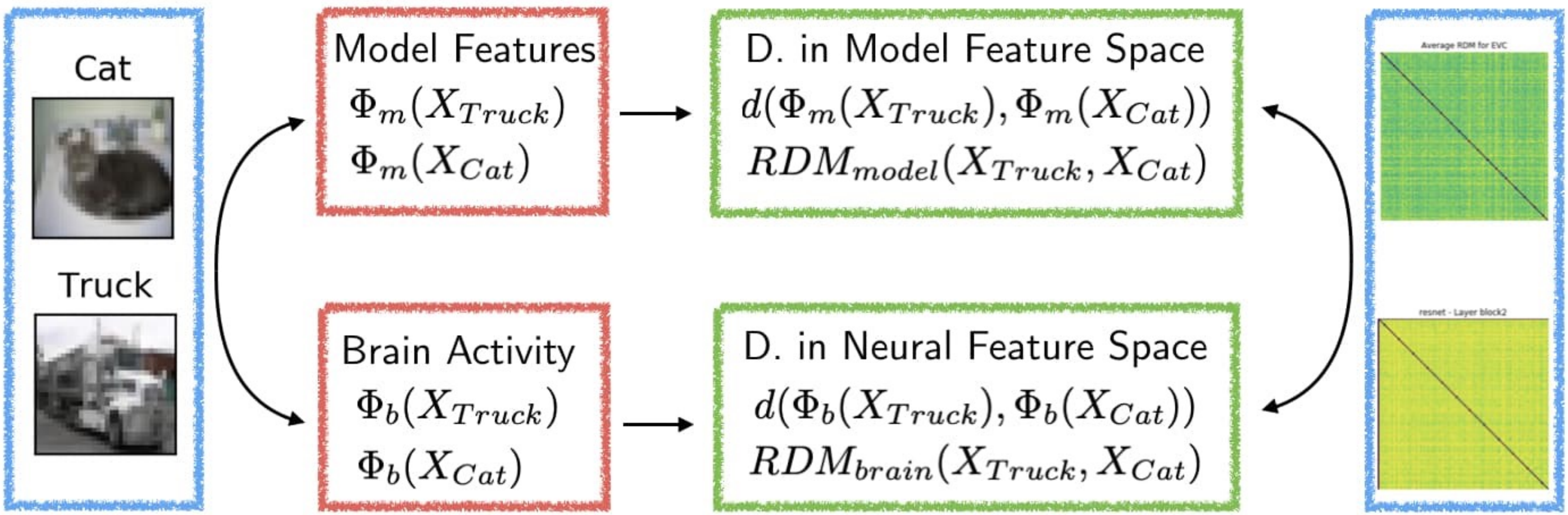
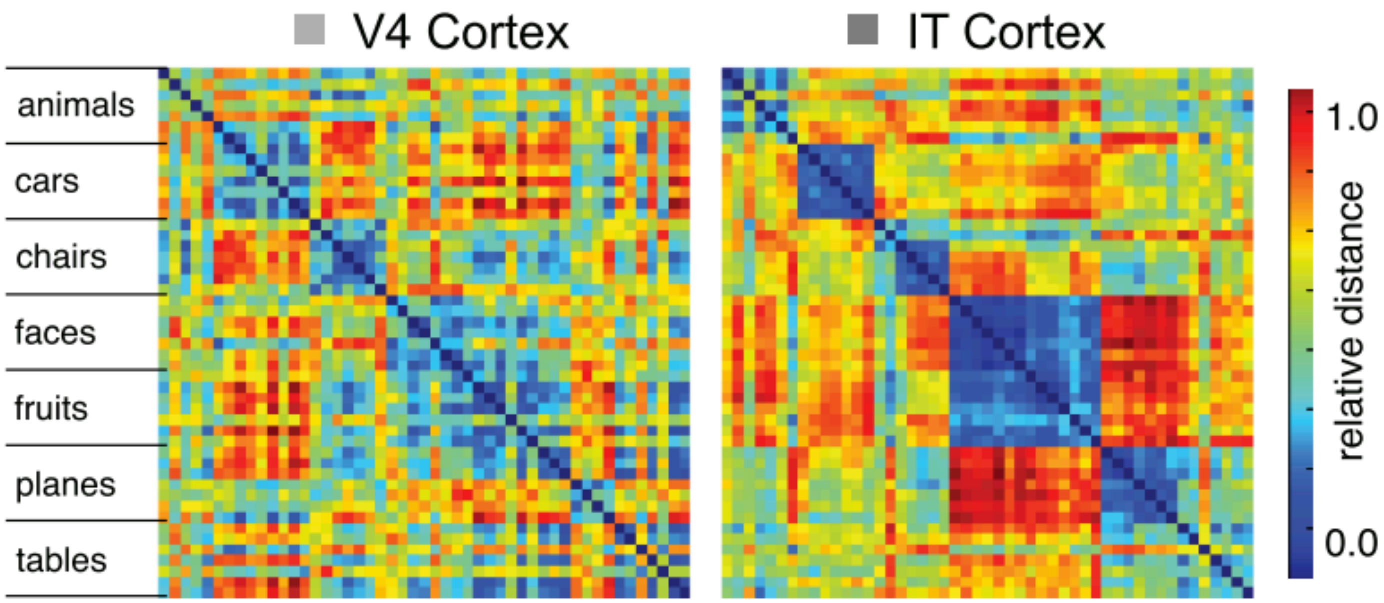
How it all started: Representational Similarity Analysis



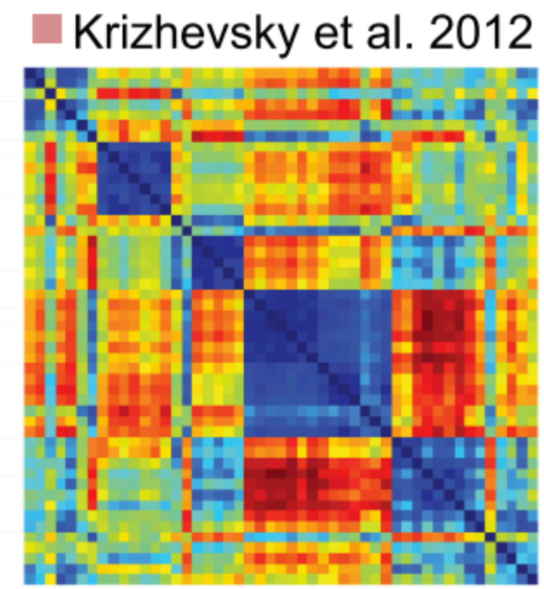
Kriegeskorte, et al (2008 - Frontiers in Systems Neuroscience)

CNNs Predict Time-Averaged Neural Responses

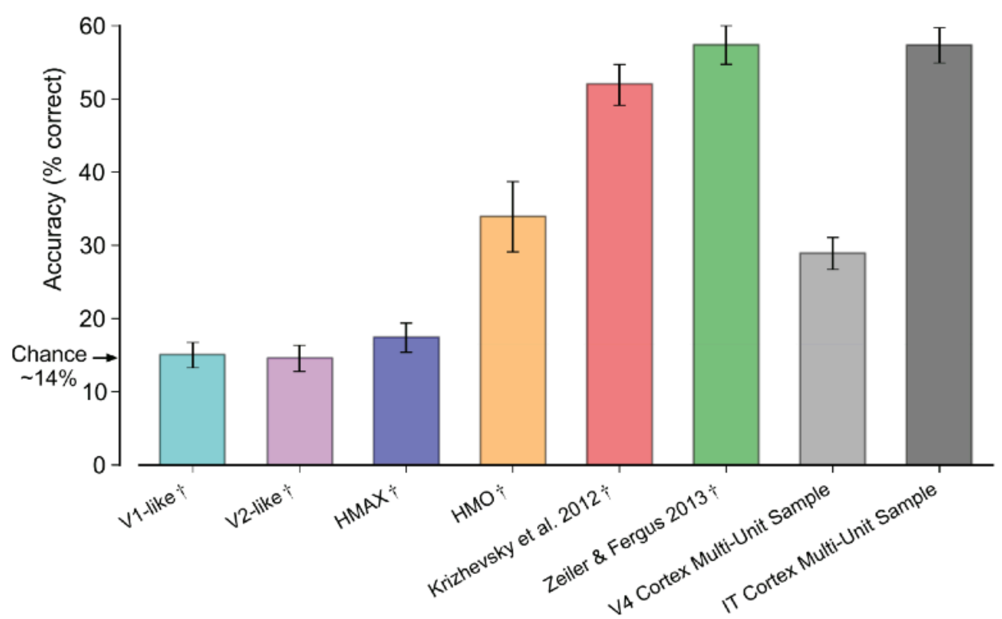
Cadieu et al. (2014 - PLoS CompBio) & Yamins et al. (2014 - PNAS)



Neural Representations



AlexNet Representations



Using Features/Activity to Classify

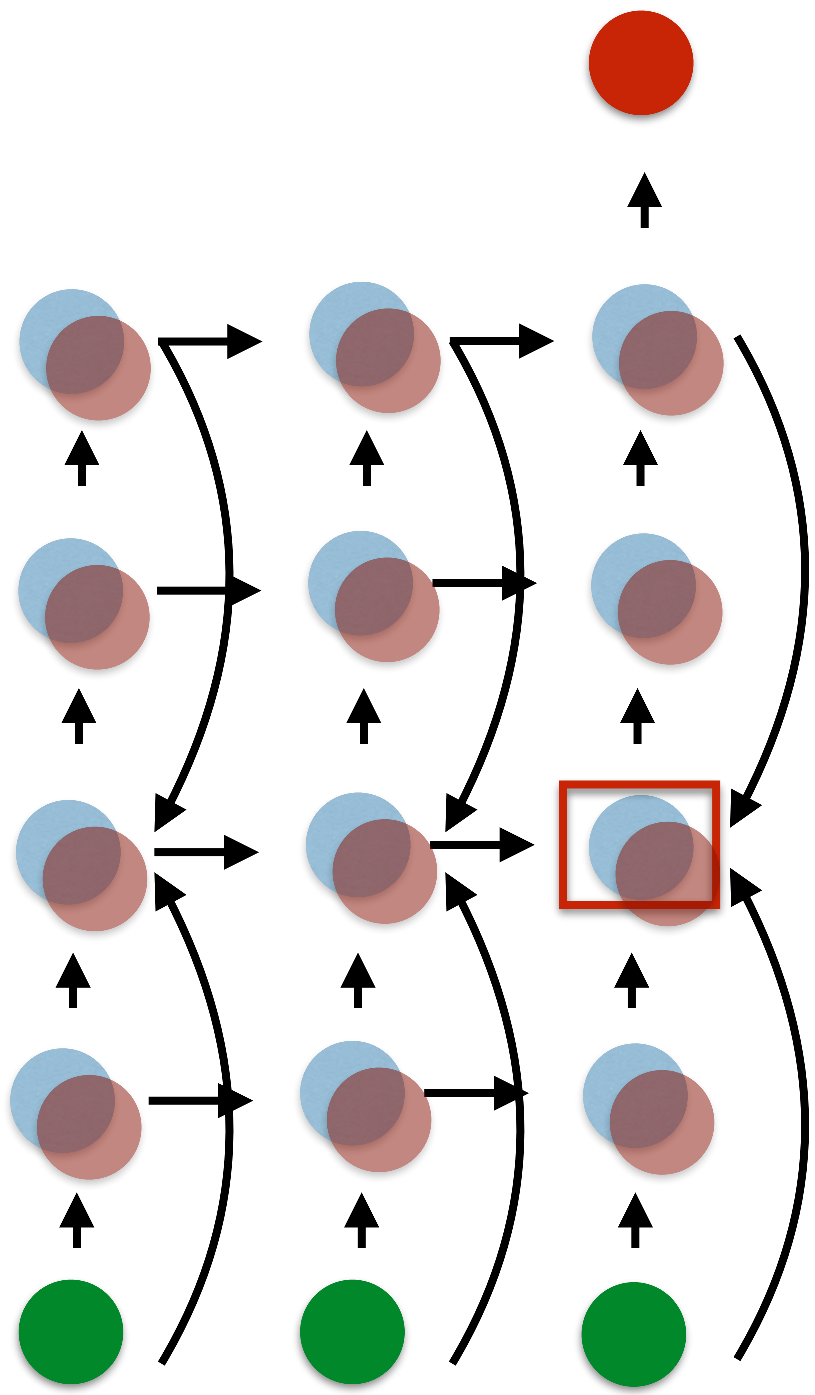
A lot of follow up work!

But: No temporal dynamics!

This paper:

1. Local recurrence
2. Long-range feedback

Feedback & Recurrence Architecture



$$R_t^l = A_l(H_t^l)$$

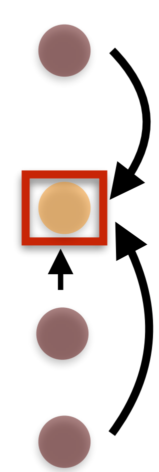
$$H_{t+1}^l = \boxed{C_l\left(\boxed{F_l(\oplus_{j\neq l} R_t^j)}, H_t^l\right)}$$

Embed FFW/FB

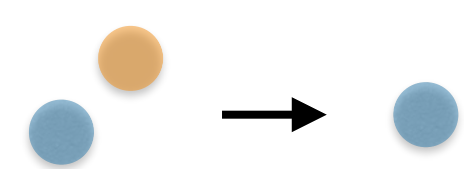
Recurrent Cell

$X_t^l :=$ $R_t^j :=$ $H_t^l :=$

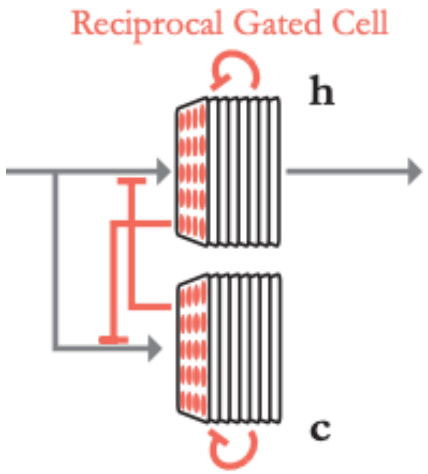
FFW/FB F^l



Recurrence C^l



Gradient flow via Gating & Bypassing



$$H_{t+1}^l, c_{t+1}^l := C^l(X_t^l, H_t^l, c_t^l; \phi)$$

$$H_{t+1}^l = f(a_t^l) \qquad c_{t+1}^l = f(\hat{c}_t^l)$$

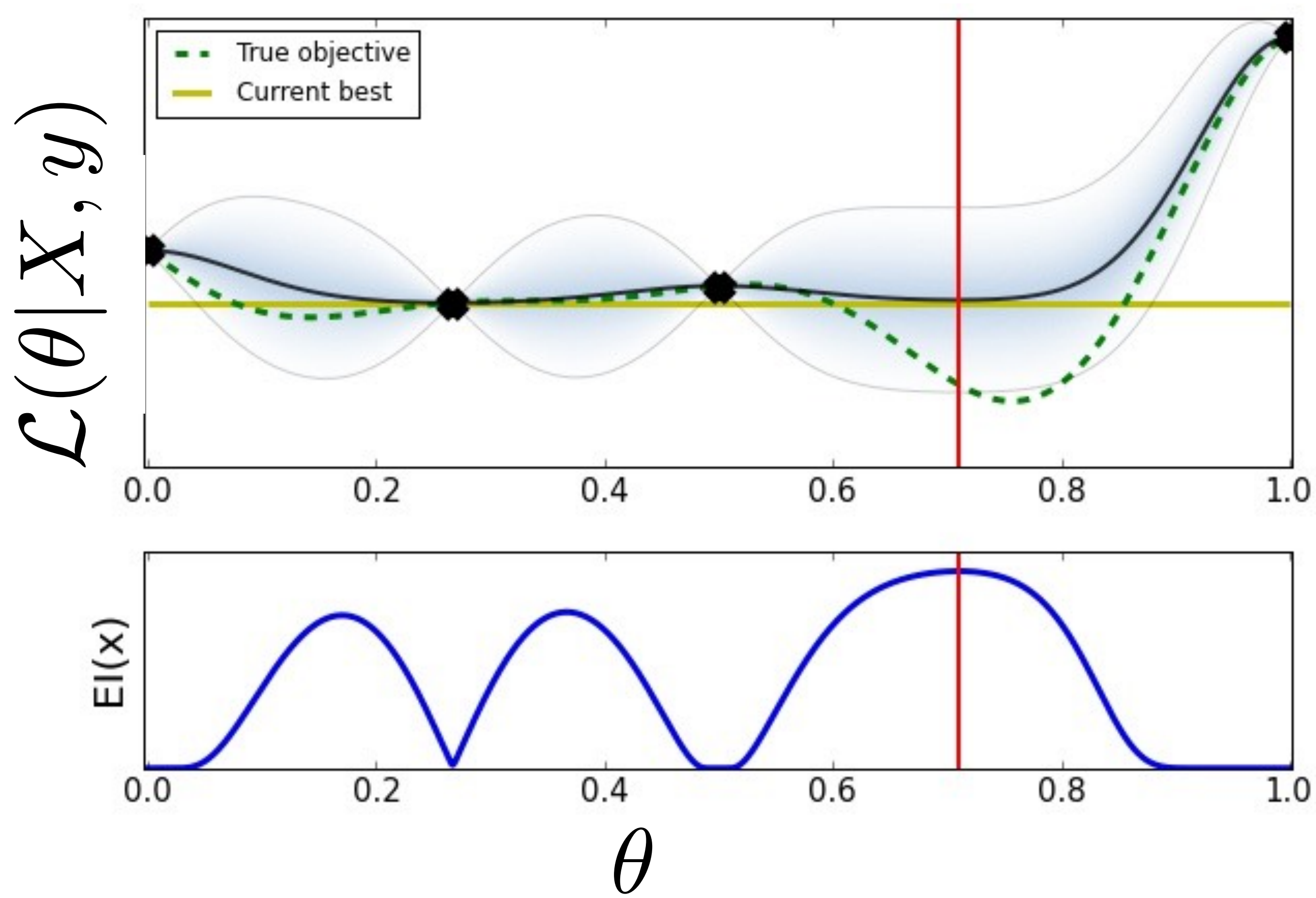
$$a_{t+1}^l = \boxed{(1 - \sigma(W_{ch} * c_t^l)) \odot X_t^l} + \boxed{(1 - \sigma(W_{hh} * H_t^l)) \odot H_t^l}$$

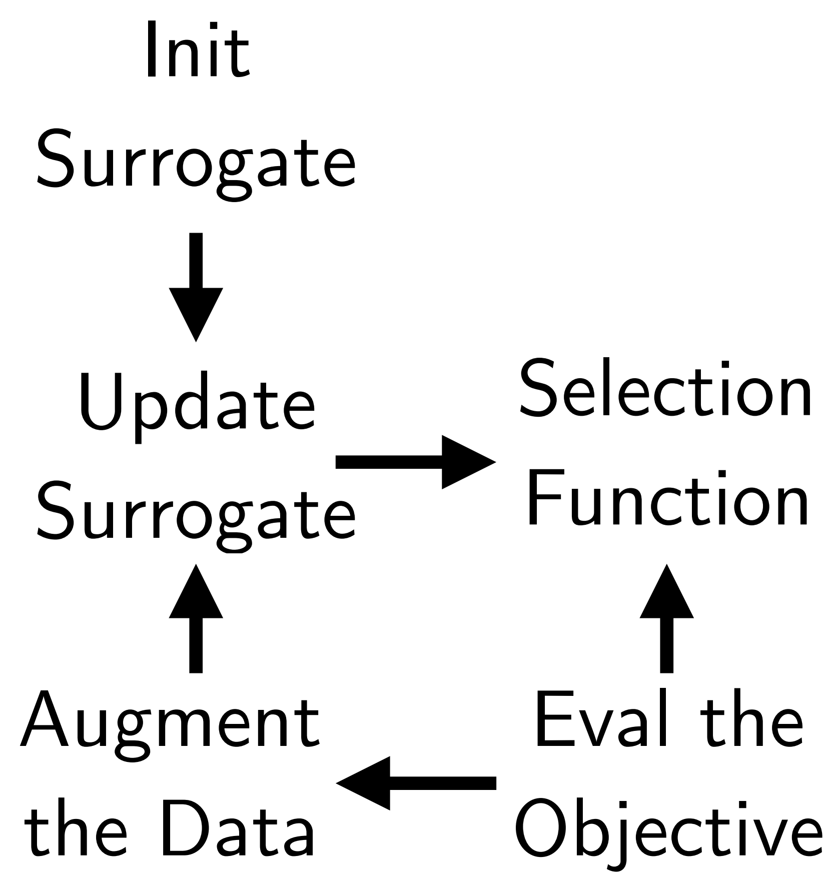
$$\hat{c}_{t+1}^l = (1 - \sigma(W_{hc} * H_t^l)) \odot X_t^l + (1 - \sigma(W_{cc} * c_t^l)) \odot c_t^l$$

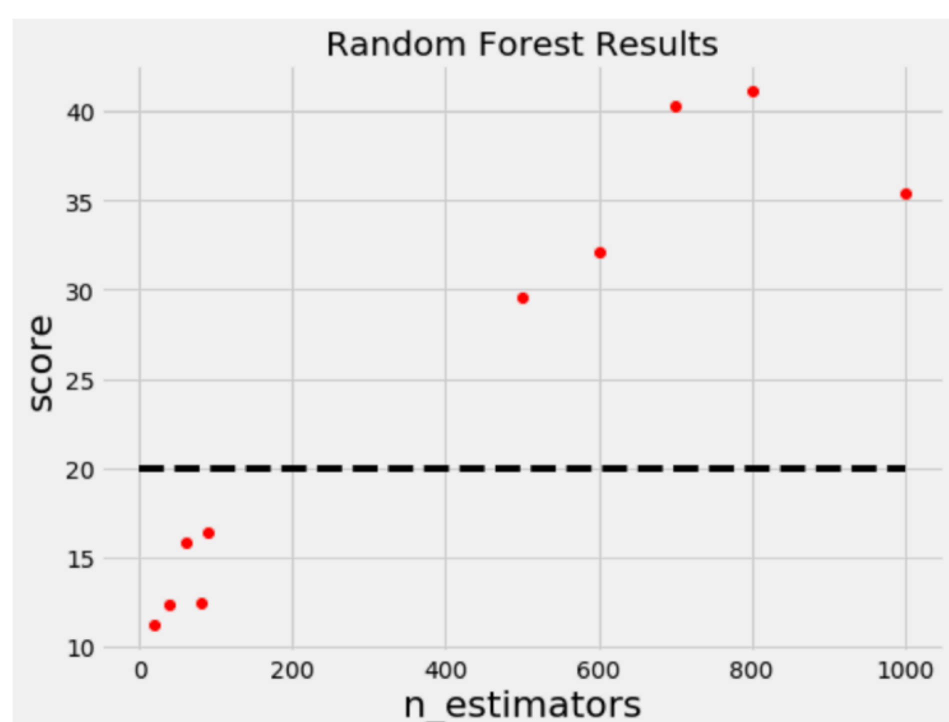
GRU Cell: $$H_{t+1}^l = \boxed{u_t^l} \odot H_t^l + (1 - u_t^l) \odot c_{t+1}^l$$

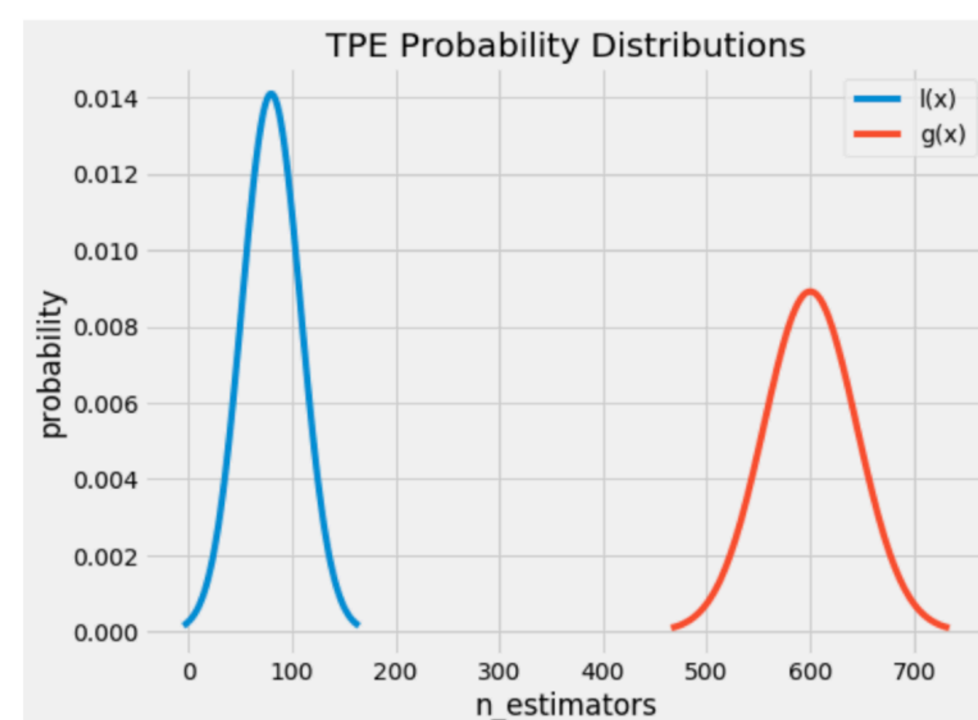
$$c_{t+1}^l = g(W_{ch}(r_t \odot H_{t-1}^l) + W_{cx} X_t^l) + b^c$$

Sequential Model-Based Optimization rocks... TPUs!



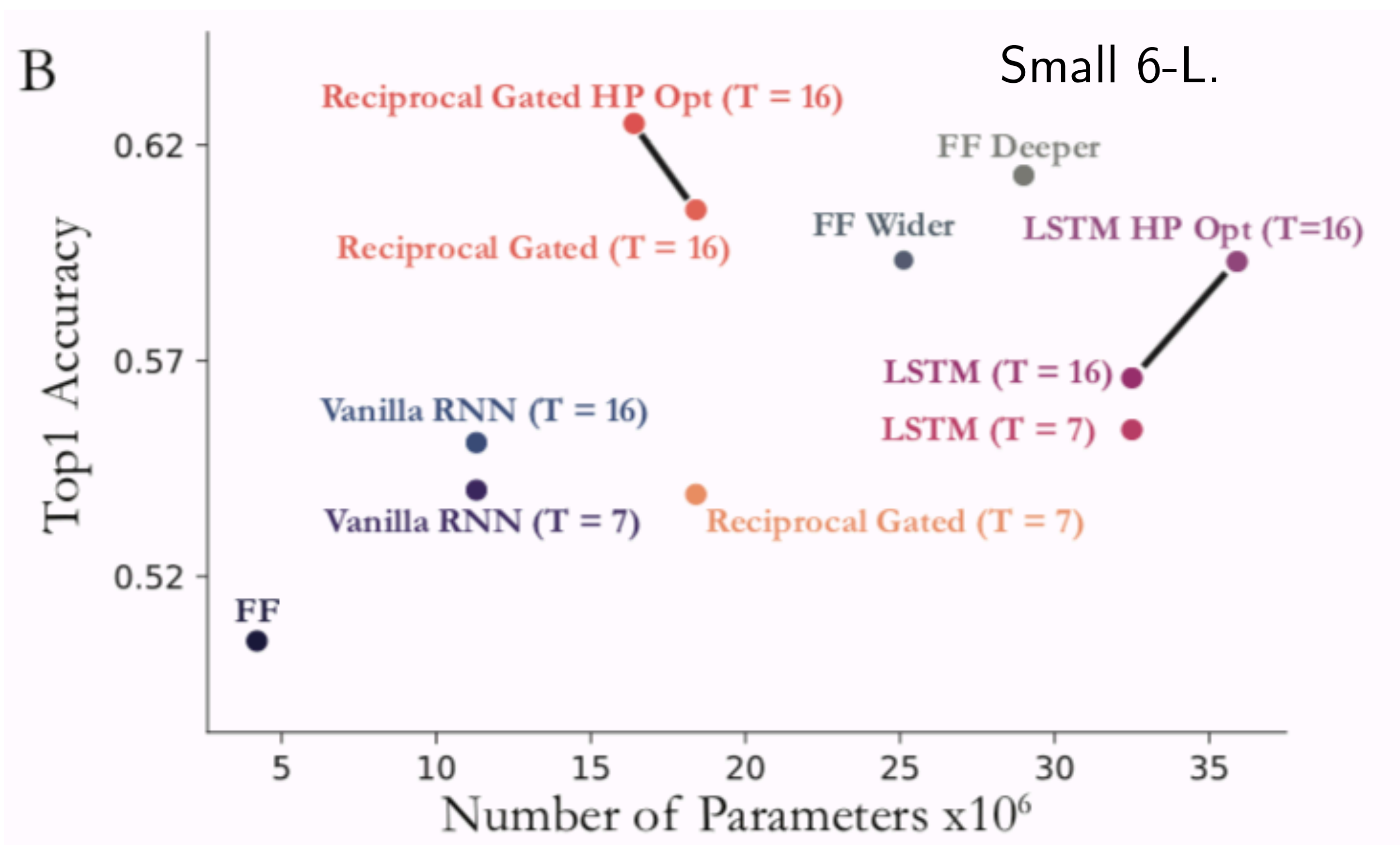


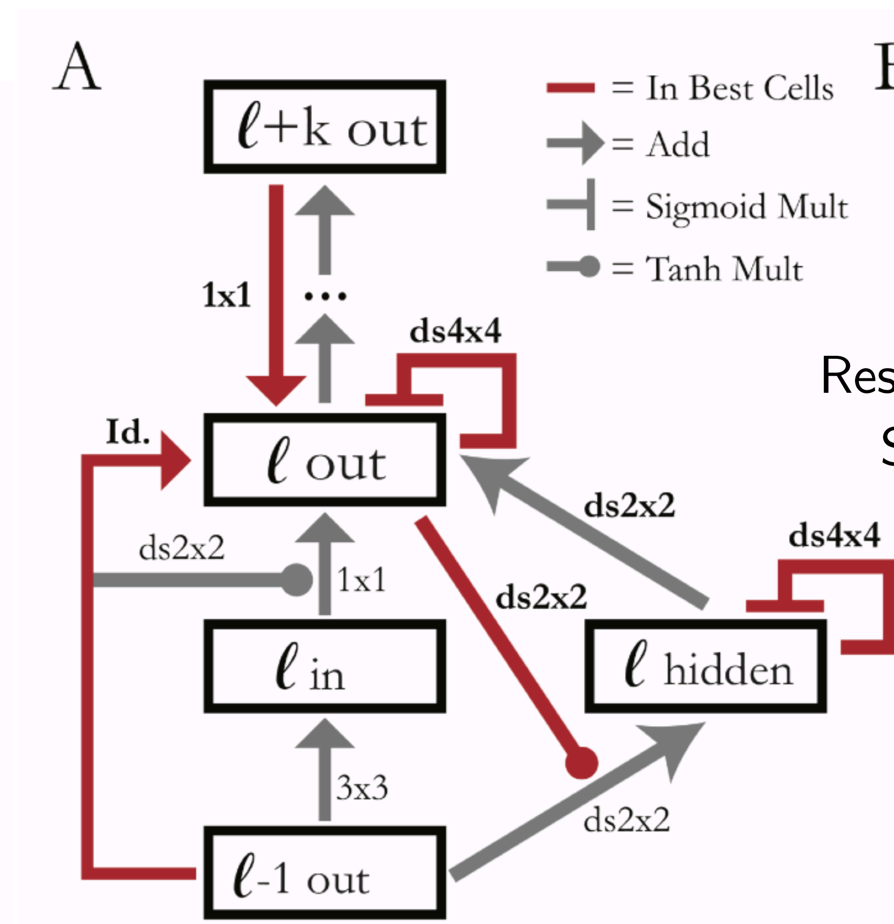




Best Models use Bypassing & Gating

- Input/Hidden State Aggregation
- Linear operations applied to input
- Non-Linearities/Activations
- Value of Biases, Lrate, Time

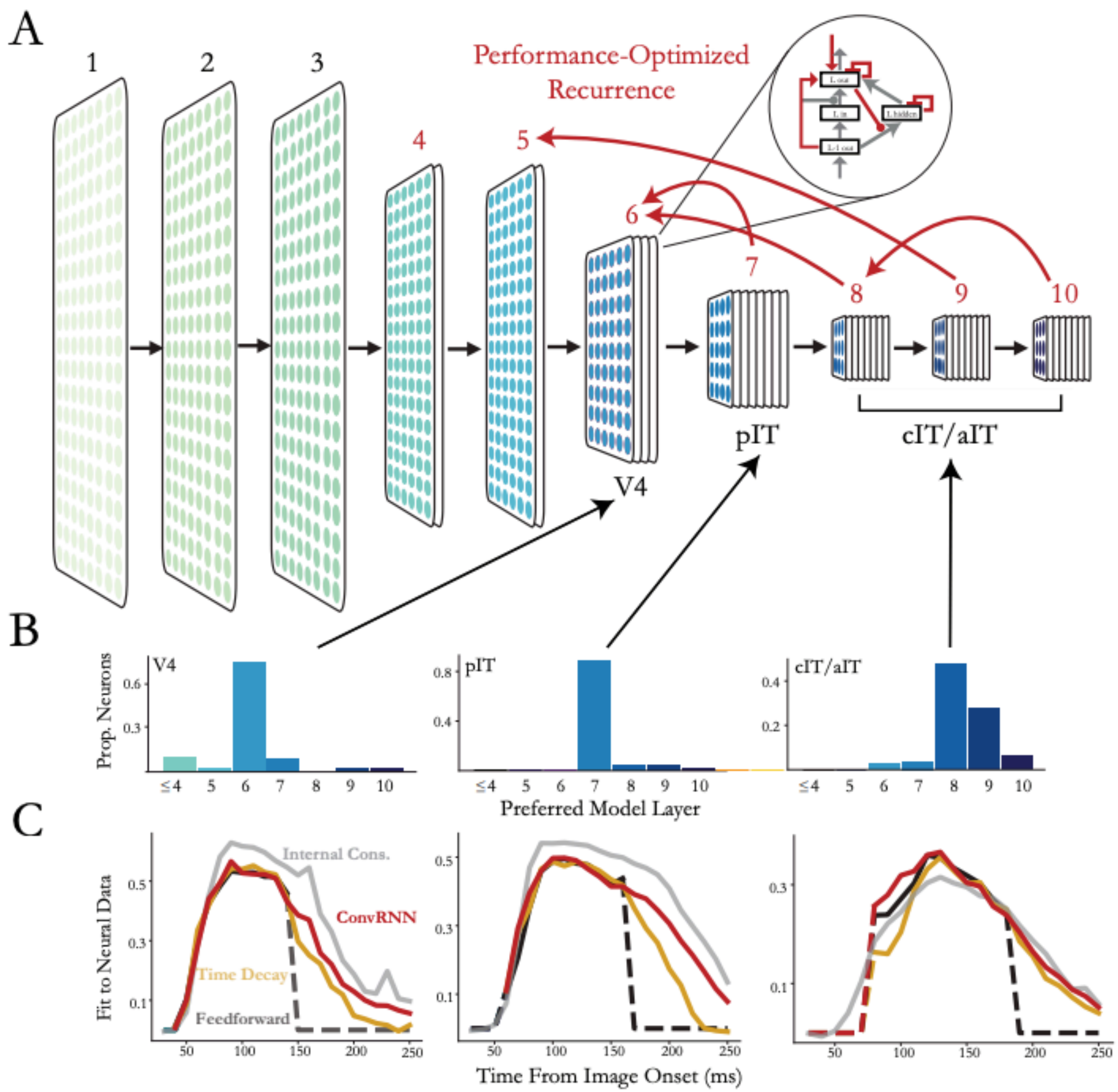




ResNet-18 Style

1. Depth-separable convolutions for updating hidden states
2. Classic convolutions for connecting bottom-up input
3. Key long-range feedback connections

Recurrence + FB Fit Late Neural Processing Dynamics



Fit linear model: determine Net L. <-> Cortex L.

Results:

1. Fitting of entire trajectory
2. Recurrence excels in later stages

Questions

1. Gating+Bypass Recurrence - Only used for gradient flow!
2. How much can we learn/predict about Neural Computations?
3. How to translate into experiments?
4. Look at Top-1 ImageNet Accuracy! How does distribution look like?

References

Bergstra, J. S., Bardenet, R., Bengio, Y., & Kégl, B. (2011). Algorithms for hyper-parameter optimization. In Advances in neural information processing systems (pp. 2546-2554).

Cadieu, Charles F., et al. "Deep neural networks rival the representation of primate IT cortex for core visual object recognition." PLoS computational biology 10.12 (2014): e1003963.

Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. Frontiers in systems neuroscience, 2, 4.

Nayebi, Aran, et al. "Task-Driven convolutional recurrent models of the visual system." Advances in Neural Information Processing Systems. 2018.

Session 3: 22nd of August 2019 (Thursday!)

TRANSFERRING KNOWLEDGE ACROSS LEARNING PROCESSES

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ABSTRACT

In complex transfer learning scenarios new tasks might not be tightly linked to previous tasks. Approaches that transfer information contained only in the final parameters of a source model will therefore struggle. Instead, transfer learning at a higher level of abstraction is needed. We propose Leap, a framework that achieves this by transferring knowledge across learning processes. We associate each task with a manifold on which the training process travels from initialization to final parameters and construct a meta-learning objective that minimizes the expected length of this path. Our framework leverages only information obtained during training and can be computed on the fly at negligible cost. We demonstrate that our framework outperforms competing methods, both in meta-learning and transfer learning, on a set of computer vision tasks. Finally, we demonstrate that Leap can transfer knowledge across learning processes in demanding reinforcement learning environments (Atari) that involve millions of gradient steps.