

1. Contribution

Learn connectivity rather than manually defining the layer structure for the task.

Brain-inspired sequence model consisting of communicating RNN modules.

Discovers skip-connections, feedback loops, and novel connectivity patterns.

- Explored dynamic and static reading mechanisms.
- Our model generalizes better and outperforms stacked GRUs on 3 sequential tasks.

2. Motivation

Neocortex often described as hierarchy but there are many side-connections and feedback loops:

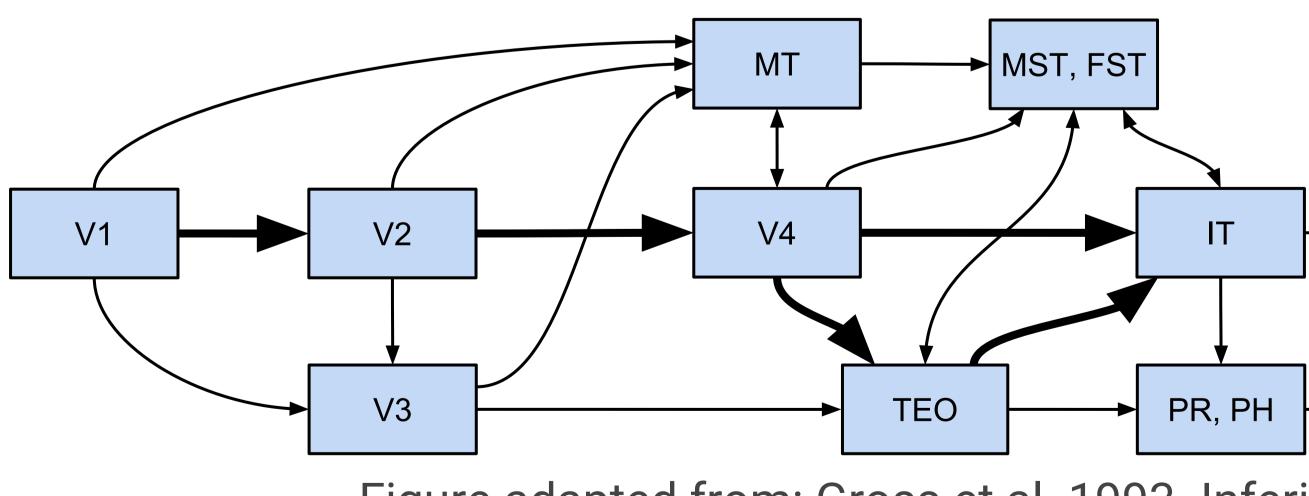


Figure adapted from: Gross et al. 1993. Inferior temporal cortex as a pattern recognition device.

Areas communicate both directly and indirectly via the thalamus. We focus on the latter here.

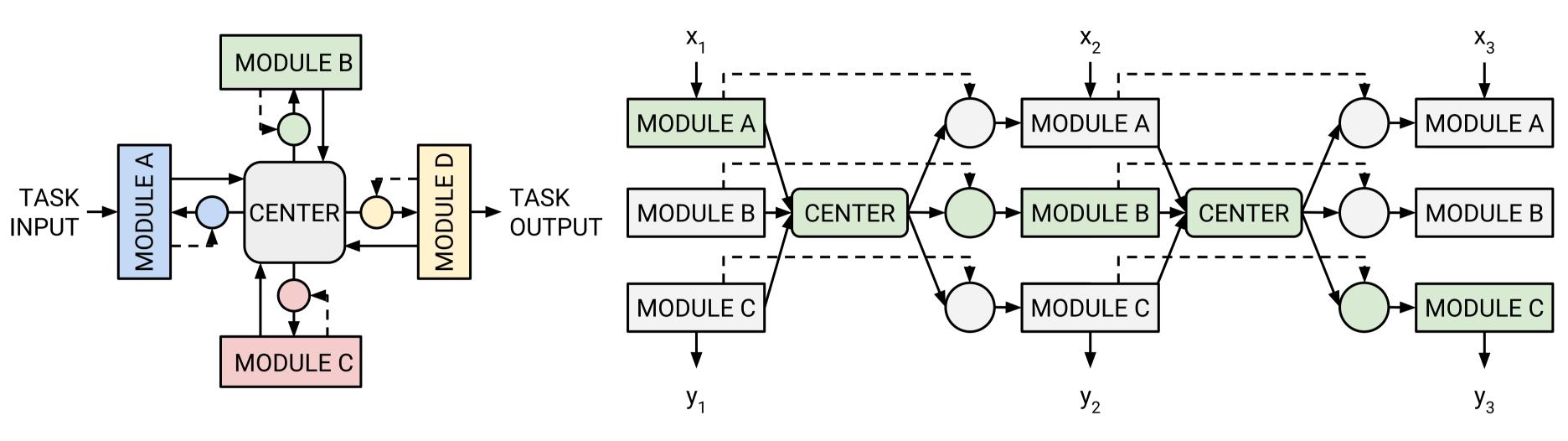
Modules communicating via a routing center include hierarchy as a special case.

Learning Hierarchical Information Flow with Recurrent Neural Modules

Danijar Hafner¹, Alex Irpan¹, James Davidson¹, Nicolas Heess² ¹ Google Brain, ² DeepMind IV NIPS 2017 #3374

3. Method: ThalNet

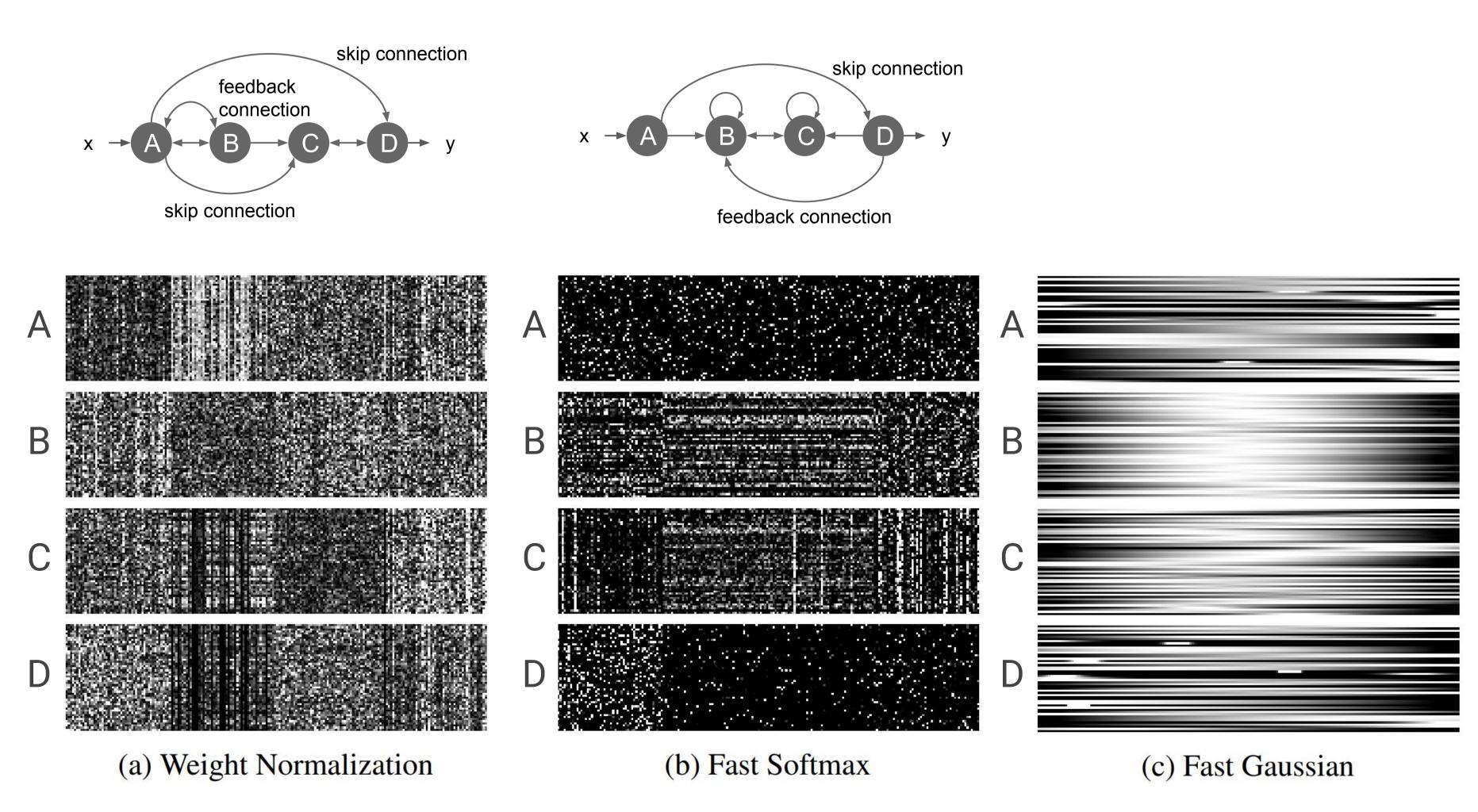
Multiple recurrent modules share their features via a routing center center (concatenation of features):



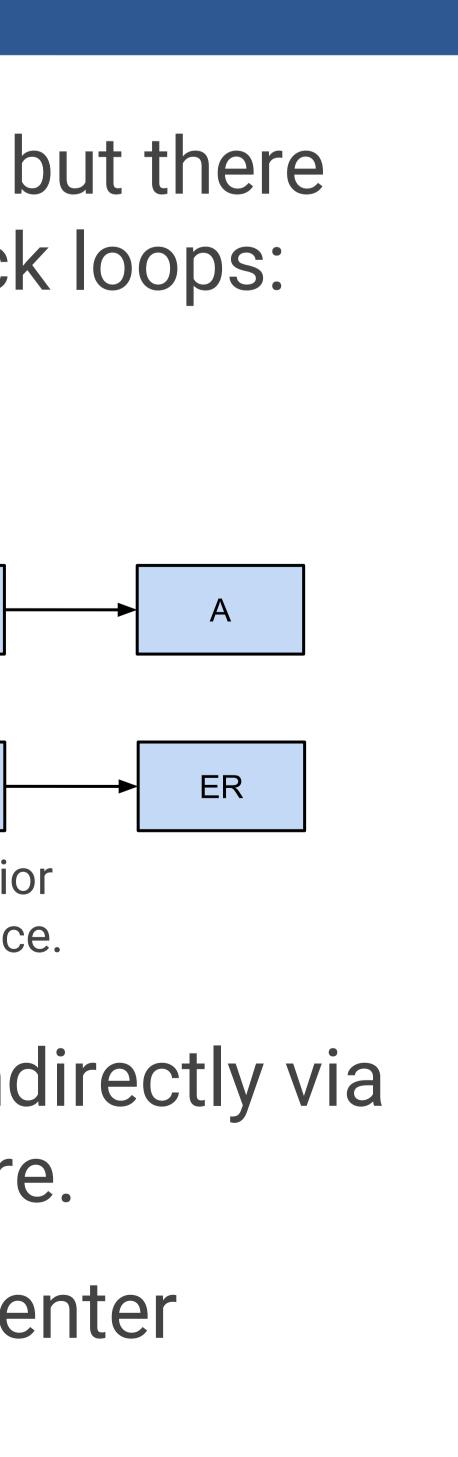
Modules observe the previous center value using dynamic or static reading mechanisms:

4. Findings

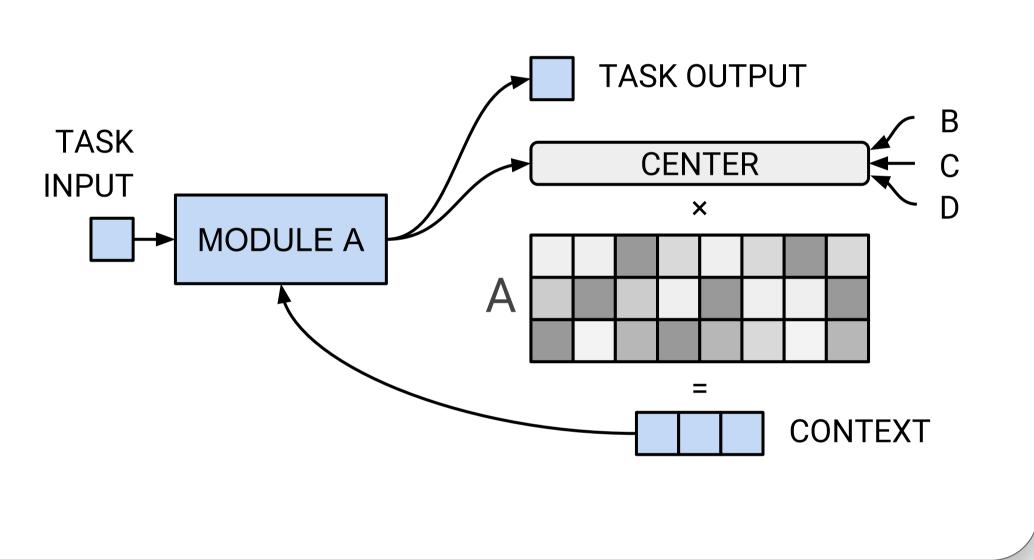
ThalNet learns hierarchical information flow, skip-connections, and long feedback pathways:

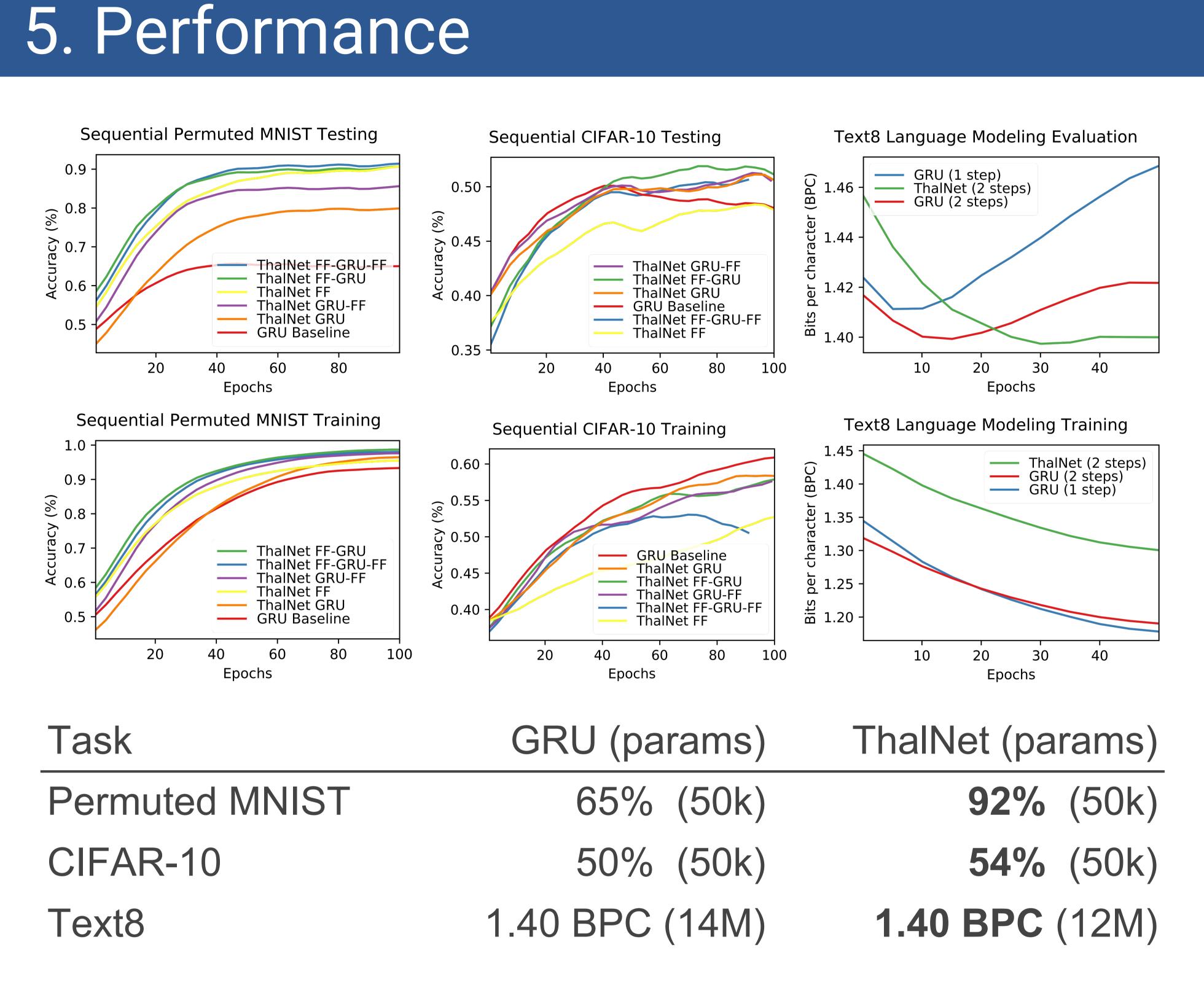


Learned reading weights for ThalNet with 4 modules and different reading mechanisms.



Possible information flow over time shown in green.

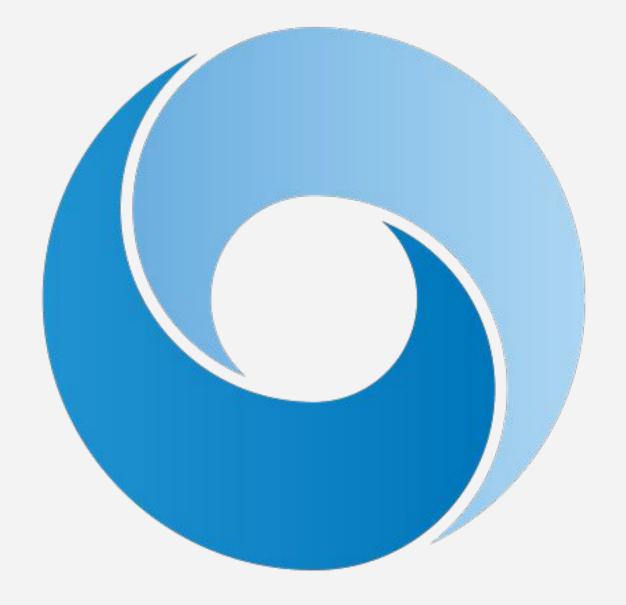




6. Conclusion

Project page: Contact:





- Similar connectivity is learned for the same task.
- Modularity and reading bottleneck regularize the model and improve generalization.
- The training time is about 2-3x that of the baseline.
- Other recurrent models might benefit from long feedback loops learned by ThalNet.
- Provides framework for multi-task learning and online architecture search.
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