Modularity as a Means for Complexity Management in Neural Networks Learning

David Castillo-Bolado Cayetano Guerra-Artal Mario Hernández-Tejera





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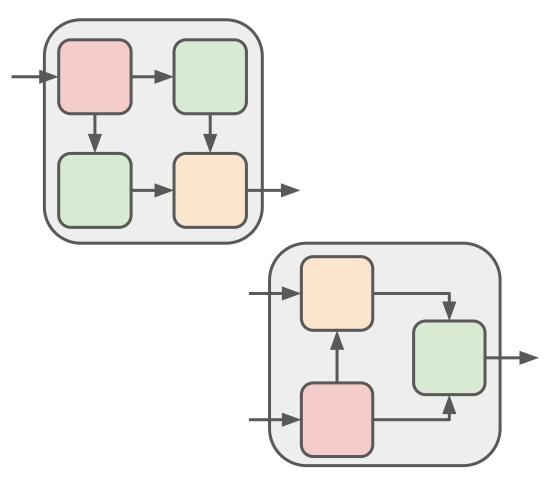
Modularity A key concept in Engineering

Modularity

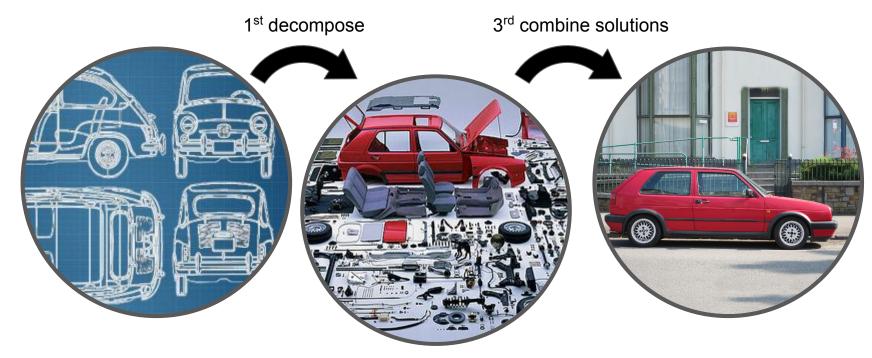
Coupling & Cohesion

Advantages

- Abstraction
- Complexity Limiting
- Reutilization

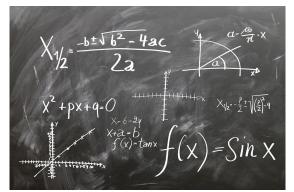


Divide & Conquer



2nd work on subproblems

The power of composition



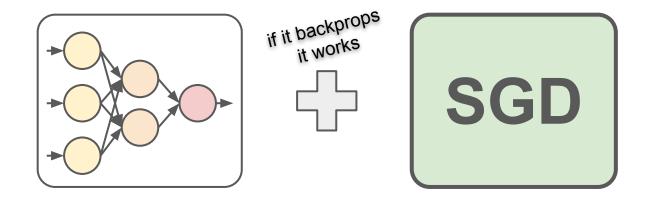


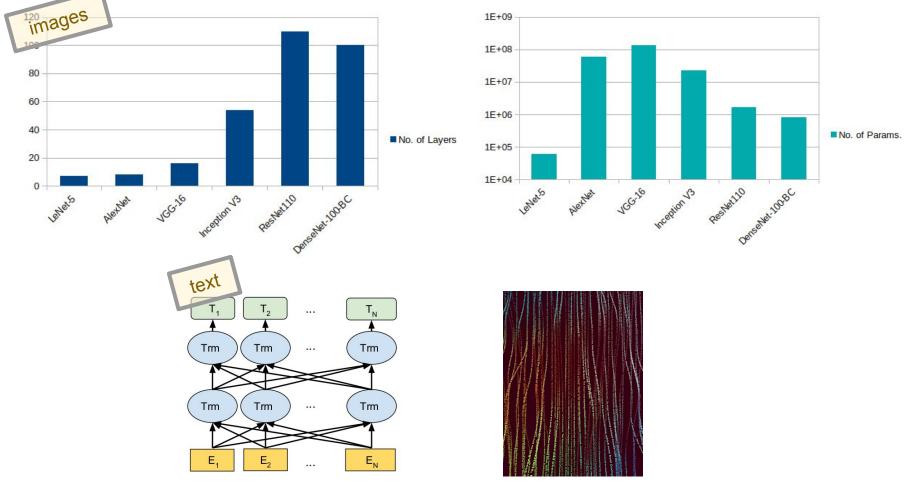




ModularityIn Neural networks

Generic approach to Neural Networks





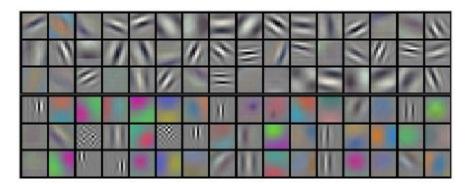
- 380M GPT-2 - 1.5G
ARGEastillo – AAAI-MAKE – 25th March 2019 – Stanford University

Modularity in Neural Networks

transfer learning / fine-tuning

instantiate the model
model <- application_resnet50(weights = 'imagenet')</pre>

word2vec



Hypothesis

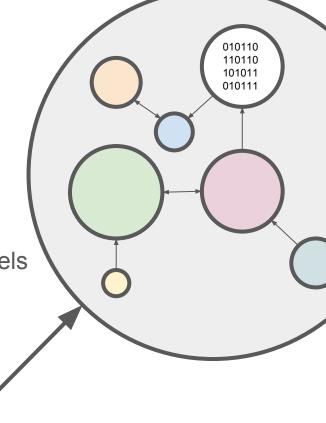
It is possible to obtain a functional equivalent of a jointly trained artificial neural network by partitioning the model and training the parts individually.

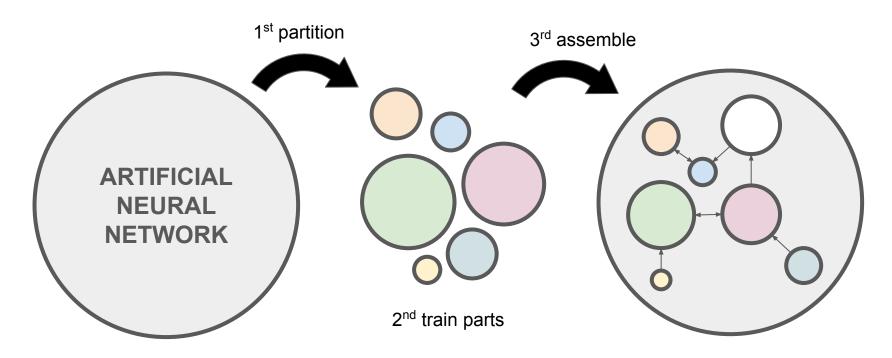
Foreseeable advantages

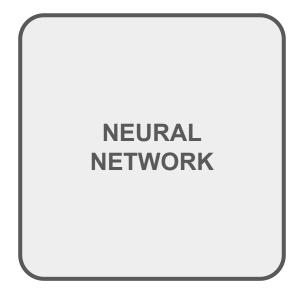
- Exploitation of parallelism at training time
- Reuse of parts among different models
- Tackle complexity by building hierarchical models
- Decoupling of parts

Concerns

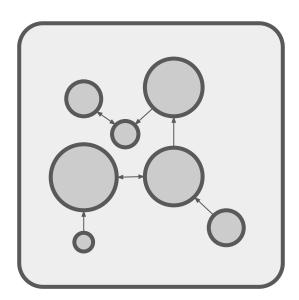
Guarantee functional equivalency



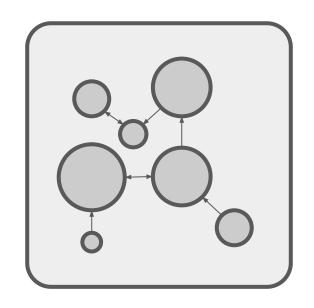


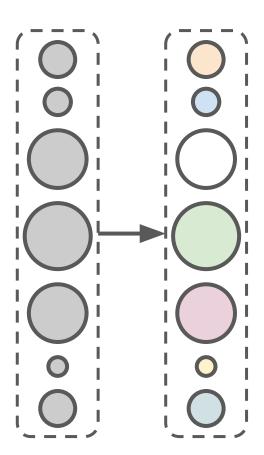


Identify modules
 1st knowledge injection

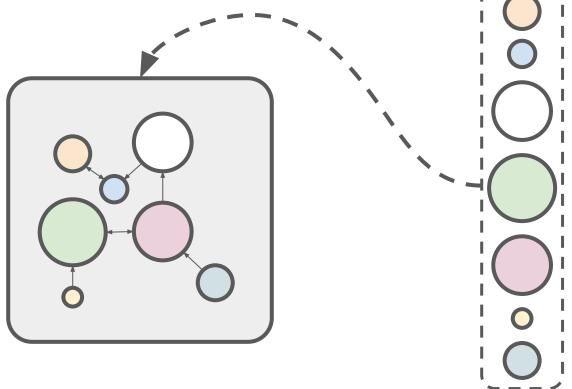


- Identify modules
 1st knowledge injection
- 2. Train modules2nd knowledge injection

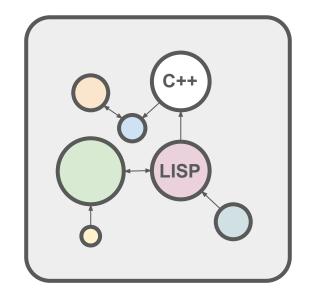


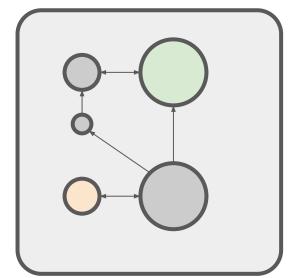


- Identify modules
 1st knowledge injection
- 2. Train modules 2nd knowledge injection
- 3. Assemble



- Identify modules
 1st knowledge injection
- 2. Train modules 2nd knowledge injection
- 3. Assemble
- 4. Reuse or Reimplementation 3rd knowledge injection



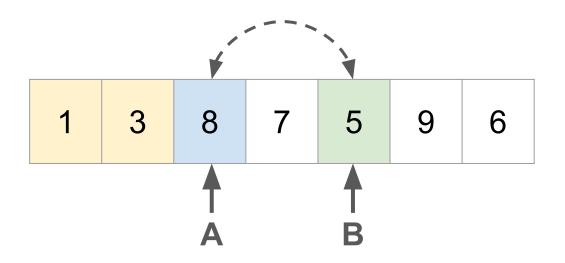


Case Study The Selection Sort Algorithm

Desiderata

- Simple implementation
- Known primitive operations
- Configurable sample complexity

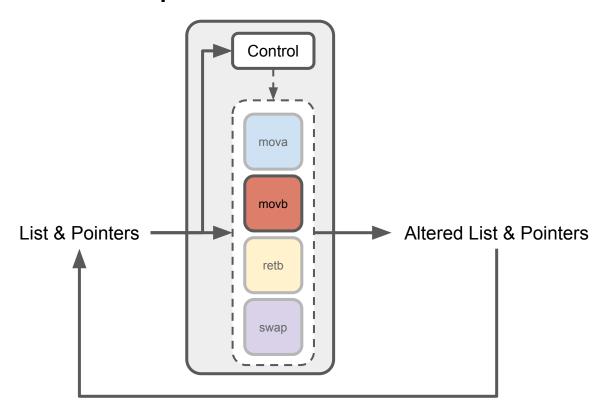
Selection Sort



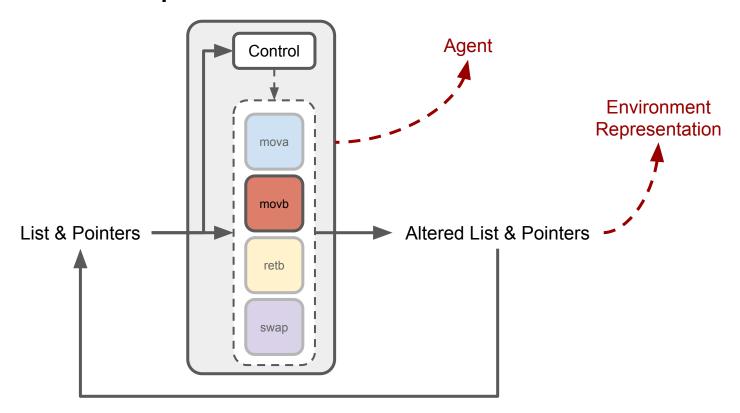
Primitive operations

- Move A to the right
- Move B to the right
- Return B right next to A
- Swap values between A and B

Selection Sort: implementation

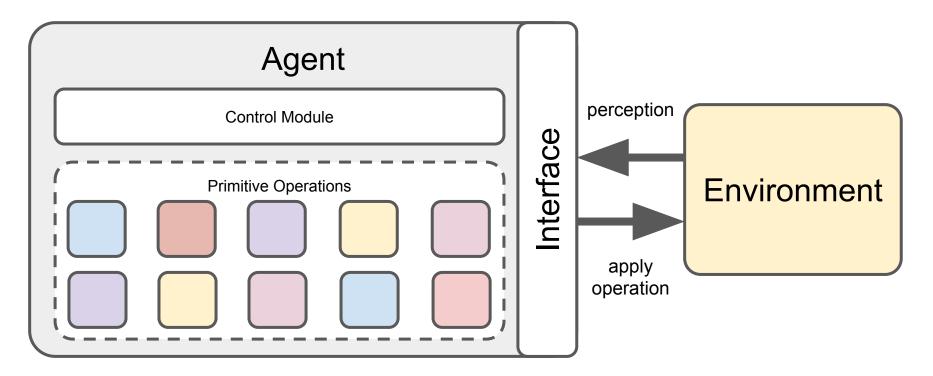


Selection Sort: implementation

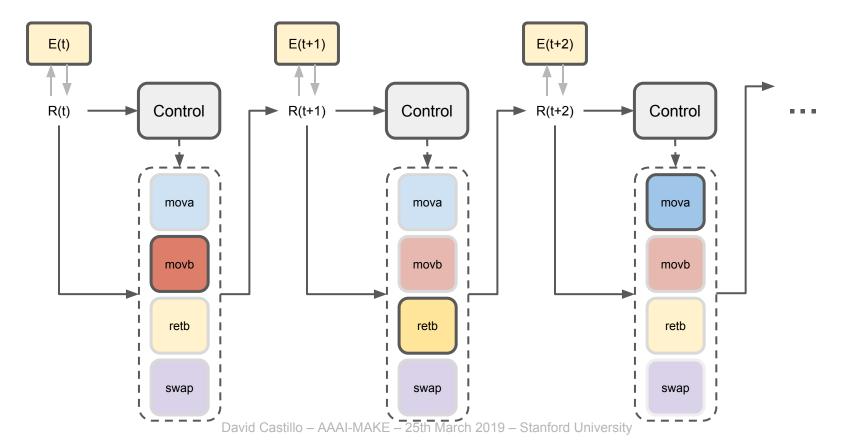


The Modular Architecture

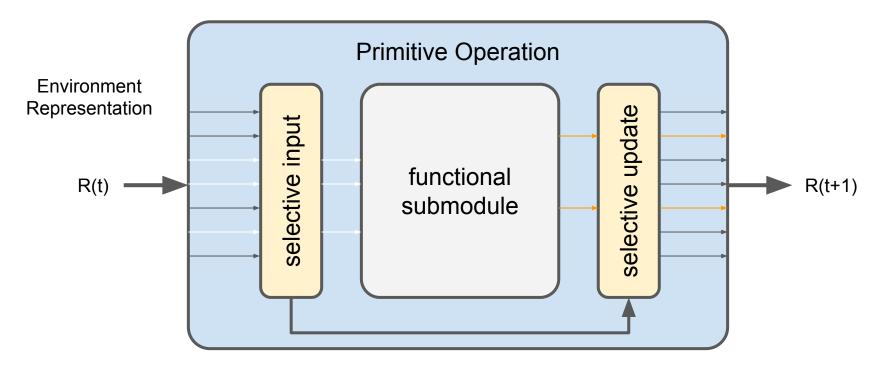
The Agent as a Problem Solver



Selection Sort: implementation

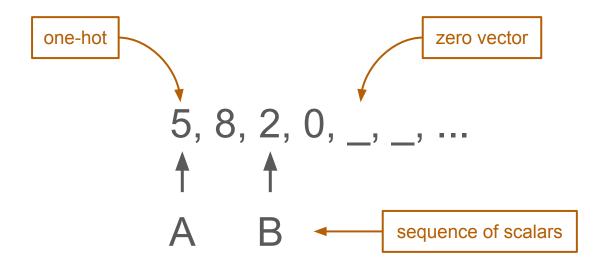


Decoupling of Functionality



Case Study Experiments

Environment Representation



Primitive operations

- Move A
- 2, 8, 5, _ A A B
- Move B
- 2, 8, 5, _ A B B
- Return B
- 2, 8, 5, _ A B B

Swap

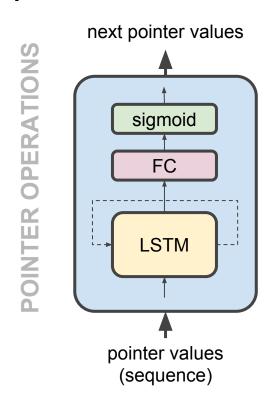
5, 8, 2, _ A B

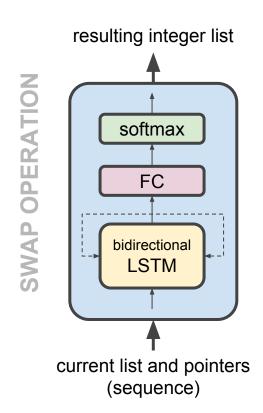
EOP

Tests

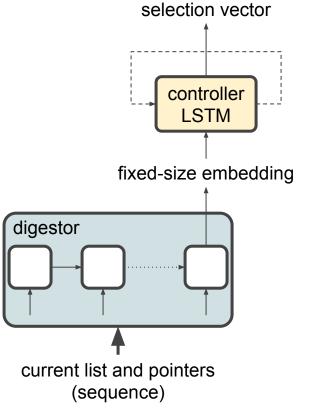
- Train & Assemble
- Monolithic training
- Time & data
- Generalization

Neural operations





The control module



Training procedure

Monolithic

- Output loss
- Selection loss
- Stop criteria: mean error rate < 0.01 & loss slope

Modular

Output loss

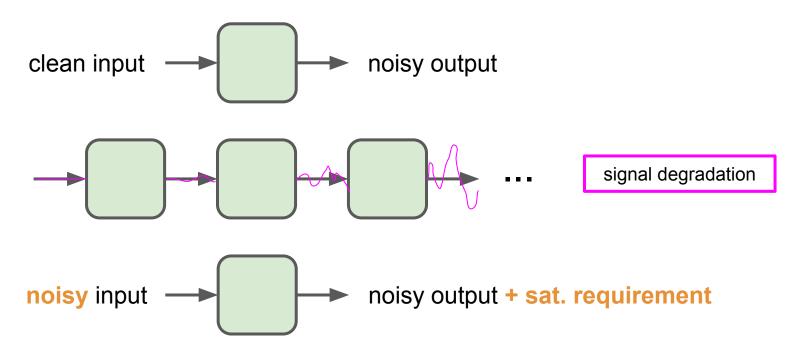
noisy input — loss

selection loss

output

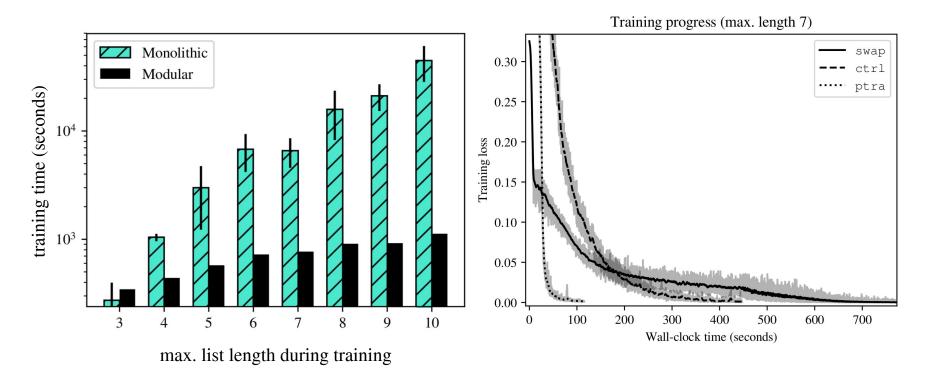
- Input noise
- Stop criteria: mean error rate < 0.01 & saturation error

Module assembly

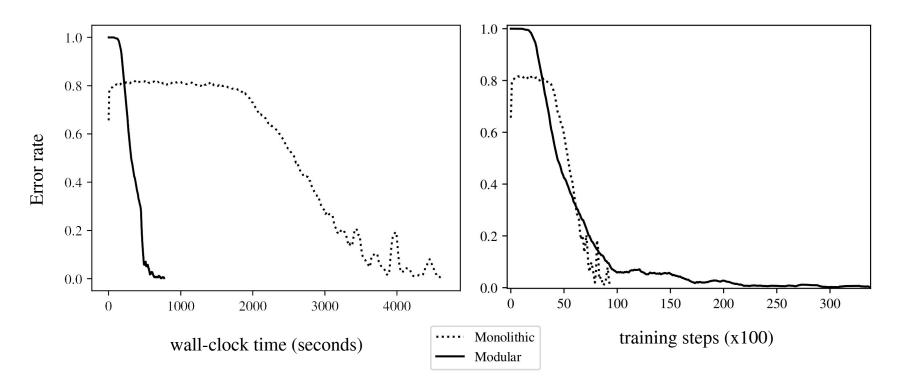


Results

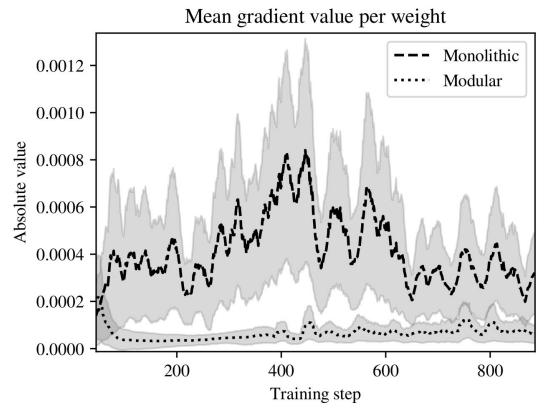
Results: training time & smoothness



Results: step efficiency

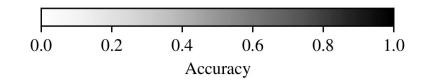


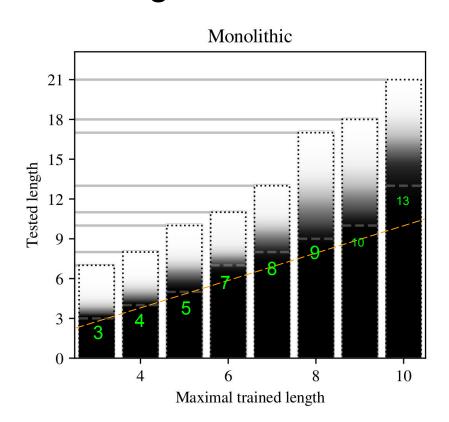
Results: gradient information

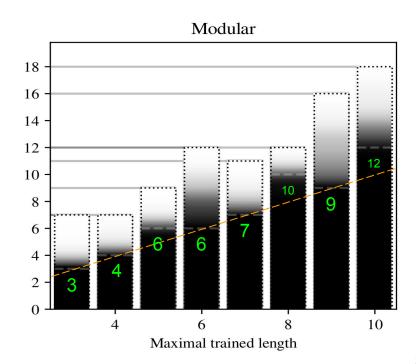


- Poorer gradient
- Higher learning rate
- Speed vs Quality

Results: generalization

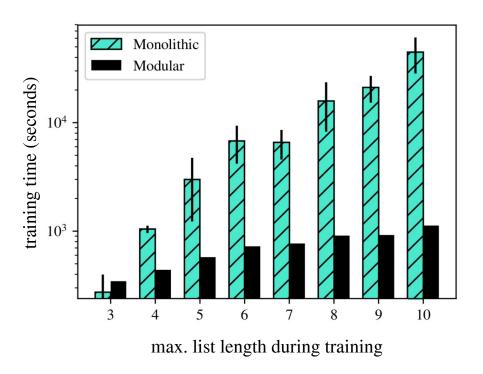




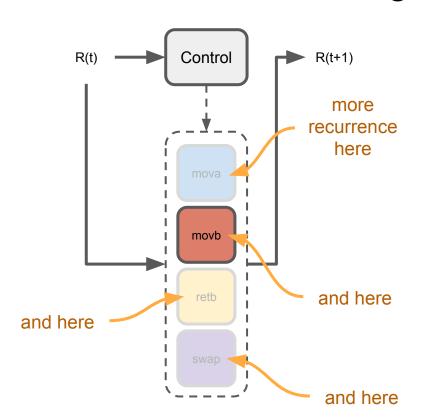


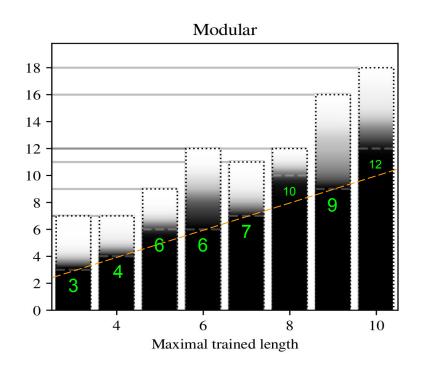
Conclusions

Conclusion 1: Time is precious

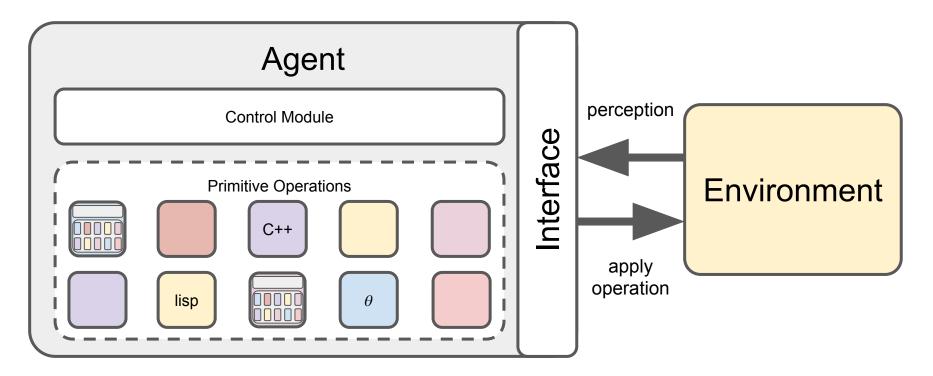


Conclusion 2: Reducing recurrence

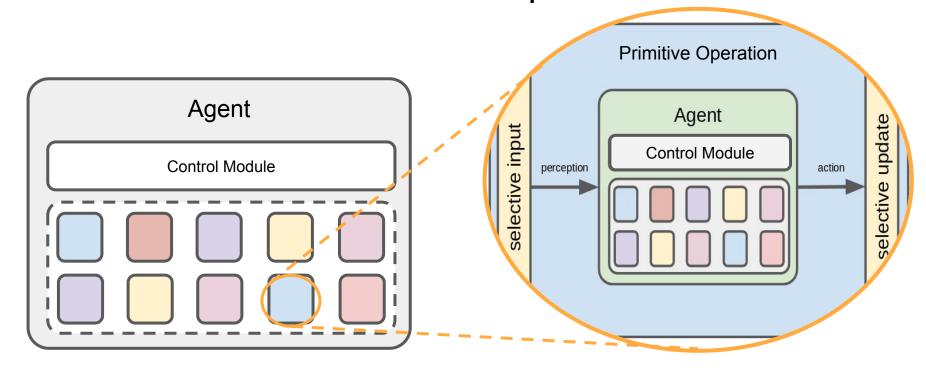




Conclusion 3: Complex Hybrid AI Systems

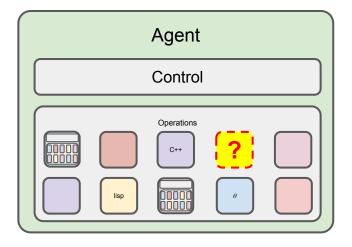


Conclusion 4: Hierarchical composition



Future research

- Transfer to state-of-the-art problems
- Reinforcement learning / Policy learning
- Reduce supervision
- Combine NNs with handcrafted modules
- Explore recursive compositionality
- Synthetic gradient for inserting blank modules



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