Investigating Recurrent Neural Network Memory Structures using Neuro-Evolution

Travis Desell (tjdvse@rit.edu)
Associate Professor
Department of Software Engineering

Co-Authors:
AbdElRahman ElSaid (PhD GRA)
Alex Ororbia (Assistant Professor, RIT Computer Science)

Collaborators:
Steven Benson, Shuchita Patwardhan, David Stadem (Microbeam Technologies, Inc.)
James Higgins, Mark Dusenbury, Brandon Wild (University of North Dakota)
Overview

• What is Neuro-Evolution?

• Background:
  • Recurrent Neural Networks for Time Series Prediction
  • Recurrent Memory Cells

• EXAMM:
  • NEAT Innovations
  • Edge and Node Mutations
  • Crossover

• Distributed Neuro-Evolution

• Results

• Future Work

• Discussion
Motivation
Neuro-Evolution

- Applying evolutionary strategies to artificial neural networks (ANNs):
  - EAs to train ANNs (weight selection)
  - EAs to design ANNs (what architecture is best?)
  - Hyperparameter optimization (what parameters do we use for our backpropagation algorithm)
Neuro-Evolution for Recurrent Neural Networks

• Most people use human-designed ANNs, selecting from a few architectures that have done well in the literature.

• No guarantees these are most optimal (e.g., in size, predictive ability, generalizability, robustness, etc).

• Recurrent edges can go back farther in time than the previous time step -- dramatically increases the search space for RNN architectures.

• With so many memory cell structures and architectures to choose from, which are best? What cells and architectures perform best, does this change across data sets and why?
Neuro-Evolution

• Applying evolutionary strategies to artificial neural networks (ANNs):
  • EAs to train ANNs (weight selection)
  • EAs to design ANNs (what architecture is best?)
  • Hyperparameter optimization (what parameters do we use for our backpropagation algorithm)

• Using NE to better understand and guide ML: what structures and architectures are evolutionarily selected and why?
Background
Recurrent Neural Networks can be extremely challenging to train due to the *explosive/vanishing gradients problem*. In short, when training a RNN over a time series (via backpropagation through time), it needs to be completely unrolled over the time series.

For the simple example above (blue arrows are forward connections, red are recurrent), backpropagating the error from time 3 reaches all the way back to input at time 0 (right). Even with this extremely simple RNN, we end up having an extremely deep network to train.
Recurrent Neural Networks

Traditionally, RNN connections go back a single time step and to the same or a previous node in the network.

This is not a requirement - they can go back multiple time steps (green) or forward in the network (orange). However it is not as well studied due to additional complexity and dramatically increasing the architectural search space.
Classification vs. Time Series Data Prediction

RNNs are perhaps more commonly used for classification (and have been mixed with CNNs for image identification). This involves outputs being fed through a softmax layer which results in probabilities for the input being a particular class. The error minimized is for the output being an incorrect class:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$  

RNNs can also be used for time series data prediction, however in this case the RNN is predicting an exact value of a time series, some number of time steps in the future. The error being minimized is typically the mean squared error (1) or mean absolute error (2). This is an important distinction.

$$\text{Error} = \frac{0.5 \times \sum (\text{Actual Vib} - \text{Predicted Vib})^2}{\text{Testing Seconds}} \quad (1)$$

$$\text{Error} = \frac{\sum \left| \text{ABS(Actual Vib} - \text{Predicted Vib}) \right|}{\text{Testing Seconds}} \quad (2)$$
"Simple" neurons are the basic neural network building block. Inputs are summed, and activation function is applied and the output is feed forward to other neurons.

Simple (and any other memory cell structure) can also have recurrent edges (in red) added through the evolutionary process. These can loop back to the same neuron (e.g., an Elman-like connection) or to any other neuron in the network (shallower, same layer or deeper).
Memory Cell Structures - LSTM

Long Short-Term Memory (LSTM) are perhaps the most well known RNN memory cell, first proposed in 1997 by Hochreiter and Schmidhuber.

This work uses the more modern version of LSTM, with peephole connections as well as omitting the output function (identity instead of tanh) [3]. This cellular structure, while conceptually appealing, is computationally complex with 11 trainable parameters (blue diamonds).

Memory Cell Structures - GRU

Gated recurrent units (GRUs) were first introduced in 2014 by Kyunghyun Cho et al. [2], which are similar to LSTM cells except without an output gate. As such it requires fewer trainable parameters than an LSTM (9).

Memory Cell Structures - MGU

Minimal gated units (MGUs) were proposed by Zhou et al. in 2016 [3]. It is another example of an effective recurrent cell with a low number of trainable parameters (6).


APA
Memory Cell Structures - UGRNN

Update gate recurrent neural networks (UGRNNs) were introduced in 2016 by Collins et al. [4]

UGRNNs are another simple model with only 6 trainable parameters.

Delta-RNN cells were first developed by Ororbia et al. in 2017 [5], and have shown to have comparable performance to other memory cells with fewer trainable parameters (6).

EXAMM: Evolutionary eXploration of Augmenting Memory Models
EXAMM

• Neuro-Evolution algorithm inspired by Neuro-Evolution of Augmenting Topologies (NEAT) [6].

• Advancement of the earlier Evolutionary Exploration of Augmenting LSTM Topologies (EXALT) [7]:
  • Progressively grows RNNs: nodes can be simple neurons or LSTMs.
  • Parallel in nature.
  • Node-level mutations not present in NEAT.
  • Uses Lamarckian/Epigenetic weight initialization - child RNNs utilize weights from their parent(s).

• Evolutionary Exploration of Augmenting Memory Models (EXAMM)
  • Based on EXALT, except with a library of memory cells. Nodes can be simple, LSTM, GRU, UGRNN, MGU, or Delta-RNNs.
  • Island-based Parallelism.
  • Mutations have further refinements from EXALT.

Edge and Node Mutations
• EXAMM always starts with a minimal feed forward network (top left) with input nodes for each input parameter fully connected to output nodes for each output parameter (no hidden nodes).
• The edge between Input 1 and Output 1 is selected to be split. A new node with innovation number (IN) 1 is created.
• Input 3 and Node IN 1 are selected to have an edge between them added.
• The edge between Input 3 and Output 1 is enabled.
Edge Mutations: Add Recurrent Edge

- A recurrent edge is added between Output 1 and Node IN 1.
Edge Mutations: Disable Edge Edge

- The edge between Input 3 and Output 1 is disabled.
Node Mutations: Add Node

- A node with IN 2 is selected to be added at a depth between the inputs & Node IN 1. Edges are randomly added to Input 2 and 3, and Node IN 1 and Output 1.

- The number of edges added is determined by calculating the mean and variance of the number of input and output edges for all other nodes in the network, and selecting randomly via a normal distribution with those means/variances.
Node Mutations: Split Node

- Node IN 1 is selected to be split. It is disabled with its input/output edges. It is split into Nodes IN 3 and 4, which get half the inputs. Both have an output edge to Output 1 since there was only one output from Node IN 1.
• Node IN 2 and 3 are selected for a merger (input/output edges are disabled). Node IN 5 is created with edges between all their inputs/outputs.
Node Mutations: Enable Node

- Node IN 1 is selected to be enabled, along with all its input and output edges.
Node Mutations: Disable Node

- Node IN 5 is selected to be disabled, along with all its input and output edges.
Clone makes no modifications at all to the parent, allowing it to continue with the back propagation process.
Crossover
Crossover creates a child RNN using all reachable nodes and edges from two parents. A node or edge is reachable if there is a path of enabled nodes and edges from an input node to it as well as a path of enabled nodes and edges from it to an output node, i.e., a node or edge is reachable if it actually affects the RNN.

- Crossover can either be intra-island or inter-island.
Crossover: Lamarckian Weight Initialization

- Initial RNN weights generated uniformly at random (between -0.5 and 0.5).
- New components (nodes/edges) are generated a normal distribution based on the average, standard deviation, and variance of the parent(s) weights.
Crossover: Lamarckian Weight Initialization

• In crossover where a node/edge exists in both parents we recombine the weights. The child weights, $w_c$, are generated by recombining the parents’ weights:

$$w_c = r(w_{p2} - w_{p1}) + w_{p1}$$

• Where $r$ is a random number $-0.5 \leq r \leq 1.5$, where $w_{p1}$ is the weight from the more fit parent, and $w_{p2}$ is the weight from the less fit parent. We can change $r$'s bounds to prefer weights near one parent over the other.
Distributed Neuro-Evolution
### Synchronous/Parallel EAs

<table>
<thead>
<tr>
<th>Population 1</th>
<th>fitness evaluation</th>
<th>Population 1</th>
<th>fitness evaluation</th>
<th>Population 1</th>
<th>fitness evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual 1</td>
<td></td>
<td>Individual 1</td>
<td></td>
<td>Individual 1</td>
<td></td>
</tr>
<tr>
<td>Individual 2</td>
<td></td>
<td>Individual 2</td>
<td></td>
<td>Individual 2</td>
<td></td>
</tr>
<tr>
<td>Individual 3</td>
<td></td>
<td>Individual 3</td>
<td></td>
<td>Individual 3</td>
<td></td>
</tr>
<tr>
<td>Individual 4</td>
<td></td>
<td>Individual 4</td>
<td></td>
<td>Individual 4</td>
<td></td>
</tr>
<tr>
<td>Individual 5</td>
<td></td>
<td>Individual 5</td>
<td></td>
<td>Individual 5</td>
<td></td>
</tr>
<tr>
<td>Individual 6</td>
<td></td>
<td>Individual 6</td>
<td></td>
<td>Individual 6</td>
<td></td>
</tr>
<tr>
<td>Individual 7</td>
<td></td>
<td>Individual 7</td>
<td></td>
<td>Individual 7</td>
<td></td>
</tr>
</tbody>
</table>

**Processor 1**
- Individual 1
- Individual 2
- Individual 3
- Individual 4
- Individual 5
- Individual 6
- Individual 7

**Processor 2**
- Individual 1
- Individual 2
- Individual 3
- Individual 4
- Individual 5
- Individual 6
- Individual 7

**Processor 3**
- Individual 1
- Individual 2
- Individual 3
- Individual 4
- Individual 5
- Individual 6
- Individual 7

- Traditional EAs generate an entire population at a time, evaluate the fitness of every individual and then generate the next population.

- This has problems in that if the population size is not evenly divisible by the number of processors available there is wasted computation. Also, the population size can't be less than the number of processors.
Synchronous/Parallel EAs

- Things are even more challenging if the fitness evaluation times of the individuals are different or even worse nondeterministic. Lots of waiting and unused cycles.
Asynchronous EAs

- The Master process keeps a "steady state" population.
- Workers independently request work (master generates new RNNs to train), calculate fitness and report results.
- No worker waits on another worker - naturally load balanced. Workers can even request a queue of work to reduce latency.
- Number of worker processes is independent of population size.
Asynchronous EAs can scale to millions of processors, whereas synchronous EAs are very limited [1].

Islands

- EXAMM uses islands, which have been shown to potentially provide superlinear speedup on some EAs [2].

- The master process keeps separate "island" populations and performs crossover within islands (intra-island crossover) or crossover between islands (inter-island crossover).

Islands

- When workers request individuals, the master process generates them from an island in a round-robin manner.
- Individuals are inserted into an island if they are better than the worst individual in that island (and the worst is removed) - Individual islands evolve/speciate faster.
- Periodically crossover happens between islands for most fit individuals, sharing information (a random individual on an island is crossed over with the best individual from another island).
Data Sets
Data Sets

- Two large-scale, real-world data from Aviation and Power industries used to evaluate EXAMM.

- 10 flights from the National General Aviation Flight Information Database (NGAFID):
  - 1-3 hours long
  - per second readings
  - 26 parameters

- 12 coal plant burners from a DOE award with Microbeam Technologies, Inc.
  - 10 days long
  - per minute readings
  - 12 parameters
## Data Sets: Coal Plant

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditioner Inlet Temp</td>
<td></td>
</tr>
<tr>
<td>Conditioner Outlet Temp</td>
<td></td>
</tr>
<tr>
<td>Coal Feeder Rate</td>
<td></td>
</tr>
<tr>
<td>Primary Air Flow</td>
<td></td>
</tr>
<tr>
<td>Primary Air Split</td>
<td></td>
</tr>
<tr>
<td>System Secondary Air Flow Total</td>
<td></td>
</tr>
<tr>
<td>Secondary Air Flow</td>
<td></td>
</tr>
<tr>
<td>Secondary Air Split</td>
<td></td>
</tr>
<tr>
<td>Tertiary Air Split</td>
<td></td>
</tr>
<tr>
<td>Total Combined Air Flow Total</td>
<td></td>
</tr>
<tr>
<td>Supplementary Fuel Flow</td>
<td></td>
</tr>
<tr>
<td>Main Flame Intensity</td>
<td></td>
</tr>
</tbody>
</table>

- Parameters are non-seasonal and correlated/dependent.
- Predicting Fuel Flow and Flame Intensity
- Data made public on github repo. Pre-normalized and anonymized.
Data Sets: NGAFID

10 data files, 26 parameters:

1. Altitude Above Ground Level (AltAGL)
2. Engine 1 Cylinder Head Temperature 1 (E1 CHT1)
3. Engine 1 Cylinder Head Temperature 2 (E1 CHT2)
4. Engine 1 Cylinder Head Temperature 3 (E1 CHT3)
5. Engine 1 Cylinder Head Temperature 4 (E1 CHT4)
6. Engine 1 Exhaust Gas Temperature 1 (E1 EGT1)
7. Engine 1 Exhaust Gas Temperature 2 (E1 EGT2)
8. Engine 1 Exhaust Gas Temperature 3 (E1 EGT3)
9. Engine 1 Exhaust Gas Temperature 4 (E1 EGT4)
10. Engine 1 Oil Pressure (E1 OilP)
11. Engine 1 Oil Temperature (E1 OilT)
12. Engine 1 Rotations Per minute (E1 RPM)
13. Fuel Quantity Left (FQtyL)
14. Fuel Quantity Right (FQtyR)
15. GndSpd - Ground Speed (GndSpd)
16. Indicated Air Speed (IAS)
17. Lateral Acceleration (LatAc)
18. Normal Acceleration (NormAc)
19. Outside Air Temperature (OAT)
20. Pitch
21. Roll
22. True Airspeed (TAS)
23. Voltage 1 (volt1)
24. Voltage 2 (volt2)
25. Vertical Speed (VSpd)
26. Vertical Speed Gs (VSpdG)

- Parameters are non-seasonal and correlated/dependent.
- Predicting RPM and Pitch
- Data made public on github repo. Non-normalized and anonymized.

The 2019 Genetic and Evolutionary Computation Conference
Prague, Czech Republic
July 13th-17th, 2019
Results
Computing Environment

- RIT Research Computing systems used to gather results.
- Compute nodes heterogeneous:
  - 10 core 2.3 GHz Intel Xeon CPU E5-2650 v3
  - 32 core 2.6 GHz AMD Opteron Processor 6282 SE
  - 48 core 2.5 GHz AMD Opteron Processor 6180 SEs
- All compute nodes ran RedHat Enterprise Linux 6.10.
- EXAMM runs utilized different compute notes as determined by RC's SLURM scheduler.
EXAMM Experimental Setup

• EXAMM run with individual memory cells, individual memory cells + simple neurons, and with all memory cells and simple neurons.

• Memory cell types:
  • Delta-RNN
  • GRU
  • LSTM
  • MGU
  • UGRNN

• K-fold cross validation (2 files per fold), 10 repeats per fold, 2 output parameters (RPM, Pitch) on NGAFID data - 1100 runs.
• K-fold cross validation (2 files per fold), 10 repeats per fold, 2 output parameters (Flame Intensity, Fuel Flow) on Coal Data - 1320 runs.

• EXALT trained 2000 RNNs for 10 epochs each, distributed across 20 processes.
• 4,840,000 RNNs trained in total in ~24,200 CPU hours
This work introduced a new neuro-evolution algorithm, Evolution-
mutations could potentially speed up EXAMM's neuro-evolution
even larger scale mutation operations, such as multi-node/layer
the mutation and recombination operators. Lastly, implementing
training metaparameters as well as what probabilities EXAMM uses
operator \[ \text{incorporating operators such as convolution (to handle video se-} \]
information for future development of neuro-evolution algorithms.

Problem, partly due to the fact that good cells may not necessarily
improvements in cell design. Results showed that cell selection does
memory cell development, as the addition of feedforward nodes
performance. The authors hope that these results will guide future
understanding cases like that of the GRU could yield

In general, while this largely bene-
large, real world time-series datasets. By using repeated
ated on the task of predicting

5 CONCLUSIONS AND FUTURE WORK

The implications of this are two fold: 1), running a neuro-evolution

determine when the network is "big enough".

- Rankings (deviations from mean) for flame intensity predictions. Lower values (higher on the chart) is better.
Fuel Flow

<table>
<thead>
<tr>
<th></th>
<th>Best Case</th>
<th>Avg. Case</th>
<th>Worst Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>-0.92643</td>
<td>LSTM</td>
<td>LSTM+simple</td>
</tr>
<tr>
<td>UGRNN+simple</td>
<td>-0.7644</td>
<td>Δ-RNN+simple</td>
<td>Δ-RNN+simple</td>
</tr>
<tr>
<td>LSTM</td>
<td>-0.70271</td>
<td>MGU+simple</td>
<td>Δ-RNN+simple</td>
</tr>
<tr>
<td>UGRNN</td>
<td>-0.66396</td>
<td>GRU+simple</td>
<td>MGU+simple</td>
</tr>
<tr>
<td>Δ-RNN</td>
<td>-0.58832</td>
<td>LSTM+simple</td>
<td>GRU+simple</td>
</tr>
<tr>
<td>MGU+simple</td>
<td>-0.41037</td>
<td>GRU</td>
<td>GRU</td>
</tr>
<tr>
<td>Δ-RNN+simple</td>
<td>-0.22068</td>
<td>all</td>
<td>all</td>
</tr>
<tr>
<td>LSTM+simple</td>
<td>-0.1125</td>
<td>MGU</td>
<td>UGRNN+simple</td>
</tr>
<tr>
<td>GRU+simple</td>
<td>0.85882</td>
<td>Δ-RNN</td>
<td>Δ-RNN</td>
</tr>
<tr>
<td>GRU</td>
<td>1.5692</td>
<td>UGRNN+simple</td>
<td>UGRNN</td>
</tr>
<tr>
<td>MGU</td>
<td>1.9613</td>
<td>UGRNN</td>
<td>UGRNN</td>
</tr>
</tbody>
</table>

• Rankings (deviations from mean) for flame intensity predictions. Lower values (higher on the chart) is better.
would produce the best performing RNNs. This may due to the fact
that, in some cases, an RNN with a small number of well trained
performance against the memory cell types most frequently selected
examining the memory cells types most correlated to improved per-
next point) – this stands as future work which can make EXAMM

<table>
<thead>
<tr>
<th>RPM</th>
<th></th>
<th>RPM</th>
<th></th>
<th>RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Case</td>
<td>Avg. Case</td>
<td>Worst Case</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GRU</td>
<td>-1.444</td>
<td>LSTM+simple</td>
<td>-1.7472</td>
<td>GRU</td>
</tr>
<tr>
<td>MGU+simple</td>
<td>-1.1012</td>
<td>MGU+simple</td>
<td>-1.2299</td>
<td>LSTM+simple</td>
</tr>
<tr>
<td>Δ-RNN</td>
<td>-1.0347</td>
<td>Δ-RNN</td>
<td>-1.0081</td>
<td>Δ-RNN+simple</td>
</tr>
<tr>
<td>LSTM+simple</td>
<td>-0.52825</td>
<td>GRU</td>
<td>-0.4433</td>
<td>MGU+simple</td>
</tr>
<tr>
<td>Δ-RNN+simple</td>
<td>-0.29348</td>
<td>Δ-RNN+simple</td>
<td>-0.069508</td>
<td>UGRNN</td>
</tr>
<tr>
<td>UGRNN</td>
<td>-0.076276</td>
<td>GRU+simple</td>
<td>0.050686</td>
<td>UGRNN+simple</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.18368</td>
<td>UGRNN</td>
<td>0.52115</td>
<td>GRU+simple</td>
</tr>
<tr>
<td>MGU</td>
<td>0.50967</td>
<td>all</td>
<td>0.76179</td>
<td>all</td>
</tr>
<tr>
<td>UGRNN+simple</td>
<td>0.9463</td>
<td>MGU</td>
<td>0.93224</td>
<td>Δ-RNN</td>
</tr>
<tr>
<td>GRU+simple</td>
<td>1.271</td>
<td>LSTM</td>
<td>1.0852</td>
<td>LSTM</td>
</tr>
<tr>
<td>all</td>
<td>1.5672</td>
<td>UGRNN+simple</td>
<td>1.147</td>
<td>MGU</td>
</tr>
</tbody>
</table>

- Rankings (deviations from mean) for flame intensity predictions. Lower values (higher on the chart) is better.
### Pitch

<table>
<thead>
<tr>
<th>Best Case</th>
<th>Avg. Case</th>
<th>Worst Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>MGU+simple</td>
<td>UGRNN+simple</td>
<td>GRU</td>
</tr>
<tr>
<td>all</td>
<td>GRU+simple</td>
<td>UGRNN+simple</td>
</tr>
<tr>
<td>LSTM+simple</td>
<td>Δ-RNN+simple</td>
<td>Δ-RNN+simple</td>
</tr>
<tr>
<td>LSTM</td>
<td>LSTM+simple</td>
<td>LSTM+simple</td>
</tr>
<tr>
<td>GRU+simple</td>
<td>GRU</td>
<td>Δ-RNN</td>
</tr>
<tr>
<td>UGRNN</td>
<td>MGU</td>
<td>LSTM</td>
</tr>
<tr>
<td>GRU</td>
<td>delta</td>
<td>UGRNN</td>
</tr>
<tr>
<td>MGU</td>
<td>MGU+simple</td>
<td>MGU+simple</td>
</tr>
<tr>
<td>Δ-RNN</td>
<td>UGRNN</td>
<td>MGU+simple</td>
</tr>
<tr>
<td>Δ-RNN+simple</td>
<td>LSTM</td>
<td>LSTM+simple</td>
</tr>
<tr>
<td>UGRNN+simple</td>
<td>all</td>
<td>GRU+simple</td>
</tr>
<tr>
<td></td>
<td>2.1345</td>
<td>2.3828</td>
</tr>
</tbody>
</table>

- Rankings (deviations from mean) for flame intensity predictions. Lower values (higher on the chart) is better.
Overall Rankings

<table>
<thead>
<tr>
<th>Overall Combined</th>
<th>Best Case</th>
<th>Avg. Case</th>
<th>Worst Case</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MGU+simple</td>
<td>LSTM+simple</td>
<td>LSTM+simple</td>
</tr>
<tr>
<td></td>
<td>-0.59051</td>
<td>-1.0538</td>
<td>-0.98141</td>
</tr>
<tr>
<td></td>
<td>LSTM+simple</td>
<td>Δ-RNN+simple</td>
<td>GRU</td>
</tr>
<tr>
<td></td>
<td>-0.53405</td>
<td>-0.90771</td>
<td>-0.6687</td>
</tr>
<tr>
<td></td>
<td>LSTM</td>
<td>MGU+simple</td>
<td>Δ-RNN+simple</td>
</tr>
<tr>
<td></td>
<td>-0.38905</td>
<td>-0.59001</td>
<td>-0.47566</td>
</tr>
<tr>
<td></td>
<td>Δ-RNN</td>
<td>GRU</td>
<td>MGU+simple</td>
</tr>
<tr>
<td></td>
<td>-0.36948</td>
<td>-0.2272</td>
<td>-0.27133</td>
</tr>
<tr>
<td></td>
<td>all</td>
<td>GRU+simple</td>
<td>all</td>
</tr>
<tr>
<td></td>
<td>-0.30824</td>
<td>-0.17974</td>
<td>0.047292</td>
</tr>
<tr>
<td></td>
<td>UGRNN</td>
<td>Δ-RNN</td>
<td>LSTM</td>
</tr>
<tr>
<td></td>
<td>-0.21446</td>
<td>-0.013211</td>
<td>0.12847</td>
</tr>
<tr>
<td></td>
<td>Δ-RNN+simple</td>
<td>UGRNN+simple</td>
<td>MGU</td>
</tr>
<tr>
<td></td>
<td>-0.067358</td>
<td>0.34556</td>
<td>0.23345</td>
</tr>
<tr>
<td></td>
<td>GRU</td>
<td>LSTM</td>
<td>UGRNN+simple</td>
</tr>
<tr>
<td></td>
<td>0.085614</td>
<td>0.39761</td>
<td>0.26059</td>
</tr>
<tr>
<td></td>
<td>UGRNN</td>
<td>MGU</td>
<td>Δ-RNN</td>
</tr>
<tr>
<td></td>
<td>0.20212</td>
<td>0.63765</td>
<td>0.26535</td>
</tr>
<tr>
<td></td>
<td>GRU+simple</td>
<td>UGRNN</td>
<td>UGRNN</td>
</tr>
<tr>
<td></td>
<td>0.9212</td>
<td>0.70542</td>
<td>0.62381</td>
</tr>
<tr>
<td></td>
<td>MGU</td>
<td>all</td>
<td>GRU+simple</td>
</tr>
<tr>
<td></td>
<td>1.2642</td>
<td>0.88541</td>
<td>0.83814</td>
</tr>
</tbody>
</table>

- Combined rankings from all 4 prediction parameters.
EXAMM Results

• No memory structure was the best.

• Delta-RNN, LSTM, and MGU tended better than GRU, and UGRNN (except in fuel flow, best avg case for pitch).

• Delta-RNNs compared competitively with LSTMs while requiring less weights (i.e., a less complex structure).
EXAMM Results

- Allowing all memory cells has risks and benefits.

- All cell types + simple neurons found the best networks in the case of fuel flow, 2nd best in the case of pitch, and 3rd best in the case of flame intensity.

- Using all memory cell types generally performed better than the mean on the best case, however performed worse in the average and worst cases.

- Allowing EXAMM to select from all possible memory cells was not entirely a bad strategy. In many cases it found the best but on average it did not do as well (most likely due to it having a much larger search space - tweaking hyperparameters for more exploration could improve this).

- **Open Question:** Can we further improve results by dynamically adapting the rates at which memory cells are generated?
EXAMM Results

- Adding simple neurons generally helped - with some notable exceptions.
  - All memory cell types improved with them except GRU.
  - Simple neurons + MGUs resulted in dramatic improvement, bringing them from some of the worst rankings to some of the best rankings (e.g., in the overall rankings for best found networks, MGU cells alone performed the worst while MGU and feedforward performed the best).

- Other cell types (LSTM and Delta-RNN) showed less of an improvement.

- This finding may highlight that the MGU cells could stand to benefit from further development.

- Even the rather simple change of allowing simple neurons can result in significant changes in RNN predictive ability. Selection of node and cell types for neuro-evolution should be done carefully.

- **Open question:** Why do GRU cells performed worse with simple neurons added? Why do MGU cells perform so much better?
EXAMM Results

• Larger networks tended to perform better, yet memory cell count correlation to MSE was not a great indicator of which cells performed the best.

• Challenges for developing neuro-evolution algorithms:
  • Compared the memory cells types most correlated to improved performance against the memory cell types most frequently selected by EXAMM.
  • EXAMM was not selecting cell types that would produce the best performing RNNs, rather cell types that provided an improvement to the population (most did) -- this can be a non-optimal choice.
  • An RNN with a small number of well trained memory cells was sufficient to yield good predictions, and adding more cells to the network only served to confuse the predictions.

• Open problems:
  • Running a neuro-evolution strategy allowing all memory cell types and then utilizing counts or correlations to select a single memory cell type for future runs may not produce the best results.
  • Dynamically tuning which memory cells are selected by a neuro-evolution strategy is more challenging since the process may not select the best cell types (e.g., when the network already has enough memory cells) -- so this would at least need to be coupled with another strategy to determine when the network is “big enough”.
Future Work

- Evolving memory cell structures.
- Allowing multiple activation functions (tanh mostly used in this work).
- Hyperparameter optimization for RNN training.
- Layer-level mutations to speed evolution.
- Self-tuning EXAMM.
- EXAMM for transfer learning: take a pre-evolved/pre-trained network and evolve it to new problems.

- Use our findings to examine and improve existing RNN memory cell structures.
Discussion/Questions?

https://github.com/travisdesell/exact
• Recent results comparing NEAT to EXAMM/EXALT on flame intensity data set.
• Min/avg/max mean squared error while training for each fold.
• Min/avg/max mean squared error while training for each fold.
• Min/avg/max mean squared error while training for each fold.
2 Layer LSTM

- Min/avg/max mean squared error while training for each fold.
• Min/avg/max mean squared error while training for each fold.
Elman

- Min/avg/max mean squared error while training for each fold.
• Min/avg/max mean squared error while training for each fold.
EXALT Results

<table>
<thead>
<tr>
<th></th>
<th>Nodes</th>
<th>Edges</th>
<th>Rec. Edges</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Layer FF</td>
<td>25</td>
<td>156</td>
<td>0</td>
<td>181</td>
</tr>
<tr>
<td>Two Layer FF</td>
<td>37</td>
<td>300</td>
<td>0</td>
<td>337</td>
</tr>
<tr>
<td>Jordan RNN</td>
<td>25</td>
<td>156</td>
<td>12</td>
<td>193</td>
</tr>
<tr>
<td>Elman RNN</td>
<td>25</td>
<td>156</td>
<td>144</td>
<td>325</td>
</tr>
<tr>
<td>One Layer LSTM</td>
<td>25</td>
<td>156</td>
<td>0</td>
<td>311</td>
</tr>
<tr>
<td>Two Layer LSTM</td>
<td>37</td>
<td>300</td>
<td>0</td>
<td>587</td>
</tr>
<tr>
<td>EXALT Best Avg.</td>
<td>14.7</td>
<td>26.2</td>
<td>14.6</td>
<td>81.5</td>
</tr>
</tbody>
</table>

- Significantly more reliable than the fixed architectures.
- Wallclock time was **faster** in terms of training time, 2-10x faster than the fixed RNNs.
- EXALT's RNNs were smaller (see above).

- However, some of the fixed RNNs did find slightly better performance in the best case across all the repeats.