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INVESTIGATING SPARSITY IN RECURRENT NEURAL NETWORKS

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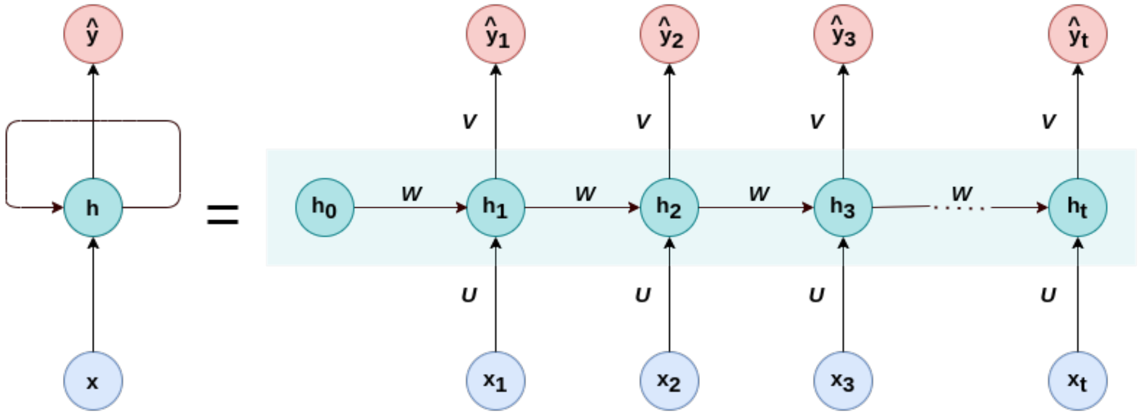
AGENDA

1. INTRODUCTION

- Recurrent Neural Networks are standard models that have shown exceptional performance in many NLP tasks that make use of **sequential information.**

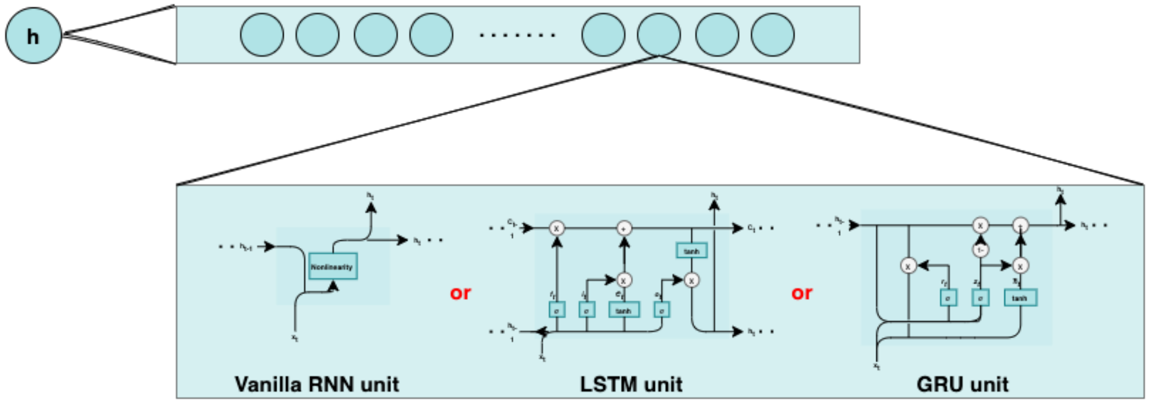


Unrolled RNN

- A standard RNN is parameterized with three weight matrices (W_{hx}, W_{hh}, W_{ho}) and two bias vectors (b_h, b_o).
- Deep extensions of such basic RNNs can be constructed by **stacking** multiple recurrent hidden states on top of each other.

1. INTRODUCTION (cont.)

- Different variations of RNNs are created based on various internal architectures of hidden states as shown below:



Internal architecture of a hidden state

- A vanilla RNN differs based on the nonlinearity function used.
- Tanh and ReLU are two of the most used nonlinearity functions.

2. MOTIVATION

- Deep Neural Networks are more likely to have increased performance but also **increased fast memory** requirements.
- One way to decrease these memory requirements is to introduce sparsity into a network's connection[1].
- Sparsity in traditional neural networks is being studied widely from the past few years but is not explored much in case of recurrent neural networks.
- Sparse structures have shown a training potential in traditional neural networks[2] which if applied to RNNs, can also make training them **less difficult** while retaining their performance.

[1] Kaiming He et al. "Deep Residual Learning for Image Recognition". In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). DOI: 10.1109/CVPR.2016.90

[2] Simon Alford et al. Pruned and Structurally Sparse Neural Networks. Tech. rep. MIT, 2018. arXiv: 1810.00299v1

3. RELATED WORK

- *Exploring Sparsity in Recurrent Neural Networks*[1] (November 2016) :
  - Pruned the linear layers that feed into the recurrent layers, the forward and backward recurrent layers and fully connected layer before the CTC layer.
- *Pruned and Structurally Sparse Neural Networks*[2] (September 2018) :
  - Tested pruning based sparse topologies by pruning a pre-trained dense network and by using RadiX-Nets.
- *Exploring Randomly Wired Neural Networks for Image Recognition*[3] (April 2019) :
  - Explored randomly wired neural networks driven by random graph models from graph theory.
- *Structural Analysis of Sparse Neural Networks*[4] (September 2019) :
  - Predicted the performance of convolutional neural networks using its structural properties.

[1] Sharan Narang et al. "Exploring Sparsity in Recurrent Neural Networks". In: ICLR 2017 Conference. arXiv: 1704.05119v2
[2] Simon Alford et al. Pruned and Structurally Sparse Neural Networks. Tech. rep. MIT, 2018. arXiv: 1810.00299v1
[3] Saining Xie et al. Exploring Randomly Wired Neural Networks for Image Recognition. Tech. rep. Facebook AI Research (FAIR), 2019. arXiv: 1904.01569v2
[4] Julian Stier and Michael Granitzer. "Structural Analysis of Sparse Neural Networks". In: 23rd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems. DOI: 10.1016/j.procs.2019.09.165

4. RESEARCH GOALS

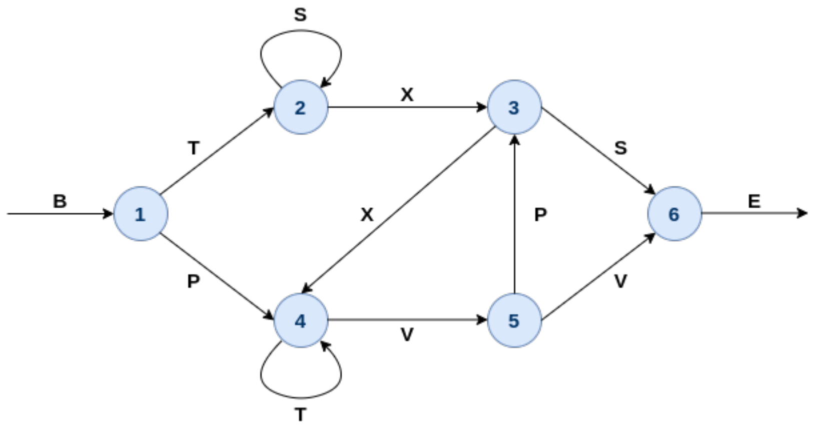
- The primary goal is to investigate, both pruned and structural sparsity in RNNs by answering the following research questions:
  1. What is the **effect of weights pruning** on a recurrent network's accuracy?
  2. What **percentage of weights pruning** is permissible without triggering a significant reduction in the performance?
  3. After pruning a certain percent of weights, if we see a significant reduction in the accuracy, how many re-training epochs can **regain accuracy**?
  4. How does a randomly structured recurrent network's **performance correlate with the graph properties** of its internal structure?
  5. Is it possible to **predict** a randomly structured recurrent network's performance using the graph properties of its base random graph?
- I will answer these questions by conducting several experiments on different datasets.

5. DATASETS

- Consists of a total of 25000 grammar sequences.
- 12500 are true Reber sequences, and 12500 are false Reber sequences.
- Train-Test split:

	Training set	Test set
True (Valid)	9339	3161
False (Invalid)	9411	3089

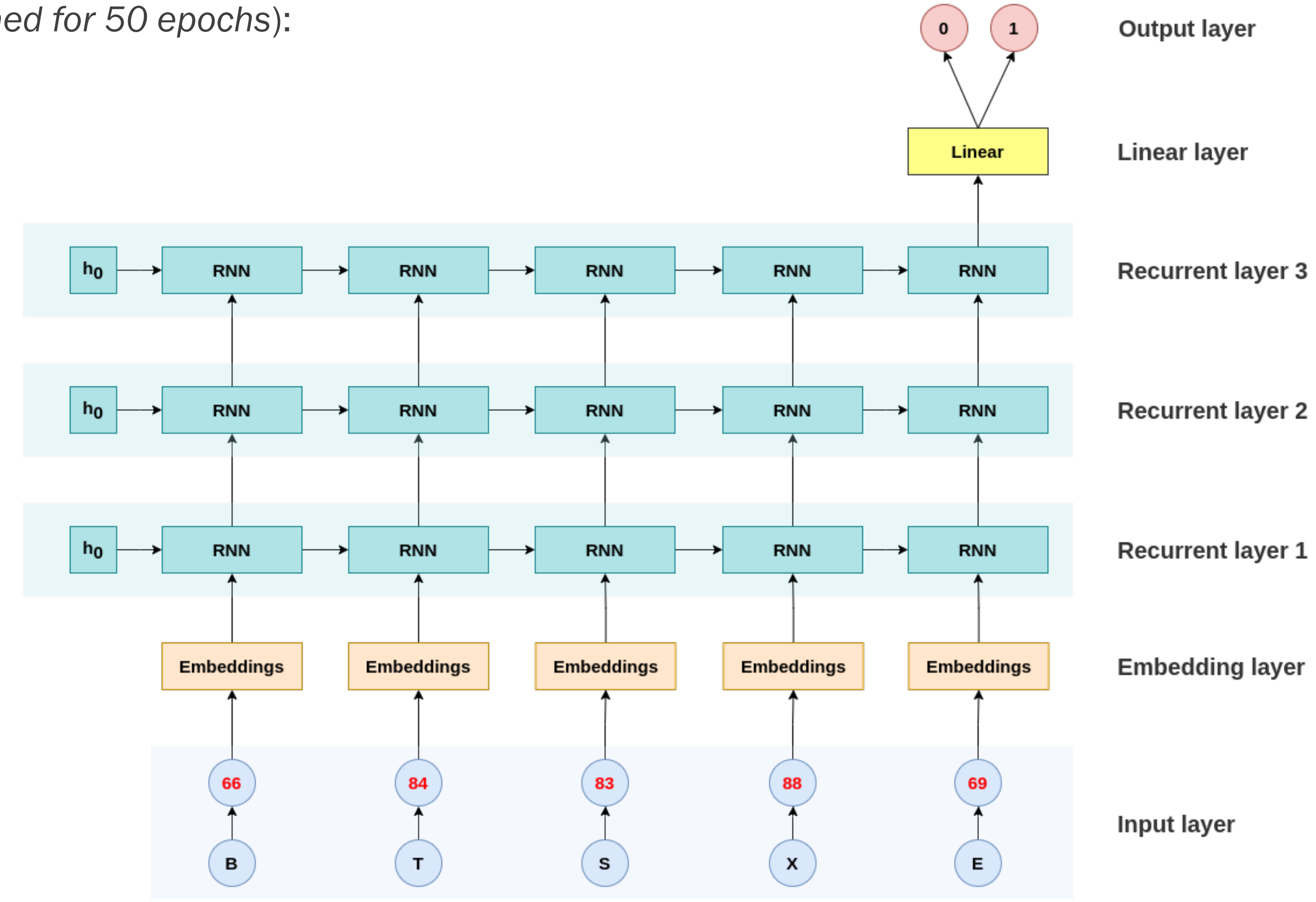
- Minimum string length: 11 (*216 strings*)
- Maximum string length: 53 (*1 string*)



Reber grammar flowchart

6. EXPERIMENTS

- Base model (*trained for 50 epochs*):



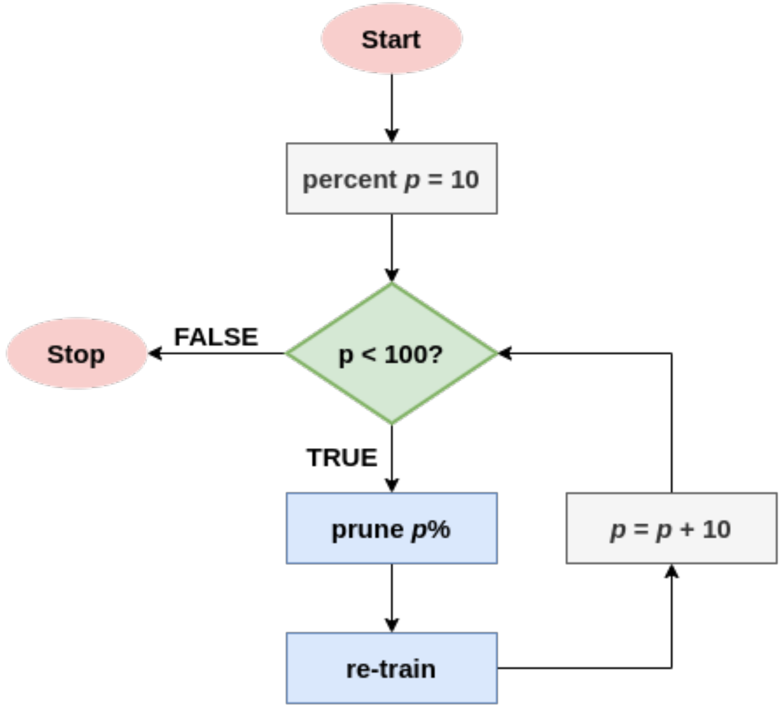
Base model

6. EXPERIMENTS (cont.)

- Pruning:
  1. Pruning both, input-to-hidden and hidden-to-hidden weights simultaneously,
  2. Pruning only input-to-hidden weights,
  3. Pruning only hidden-to-hidden weights
- Randomly structured RNN
- Performance prediction of Randomly Structured RNNs

6.1. PRUNING

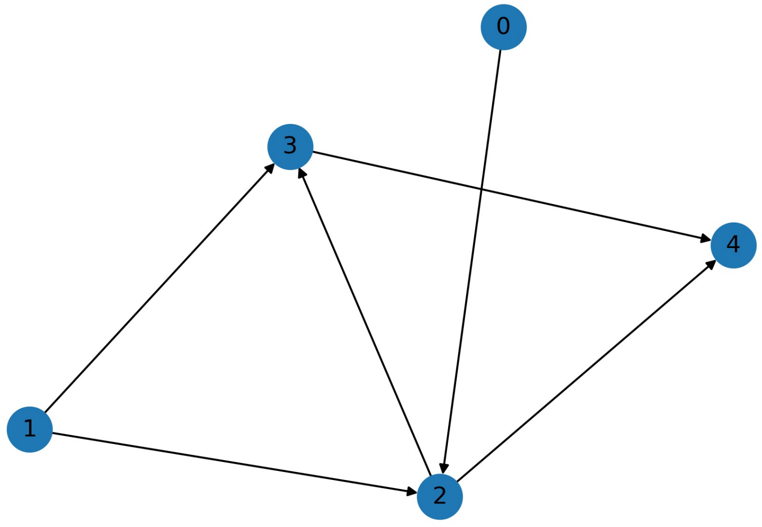
- Pruning is performed on trained base model.
- After pruning *p* percentage, pruned performance is stored.
- Afterwards, this pruned model is retrained to identify the number of epochs required to regain the accuracy.
- This pruning experiement is performed for,
    - RNN_Tanh,
    - RNN_ReLU,
    - LSTM,
    - GRU
- Results of this experiment is presented in section 1.2.



Pruning flow chart

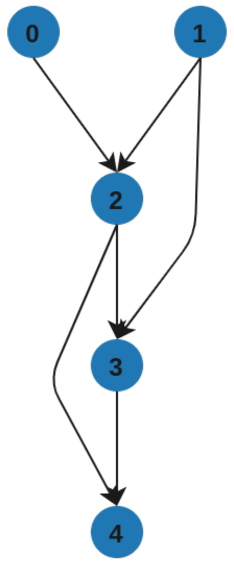
6.2. RANDOMLY STRUCTURED RNN

- Start with a Random Graph and make it directed (*if not!*).



Directed random graph

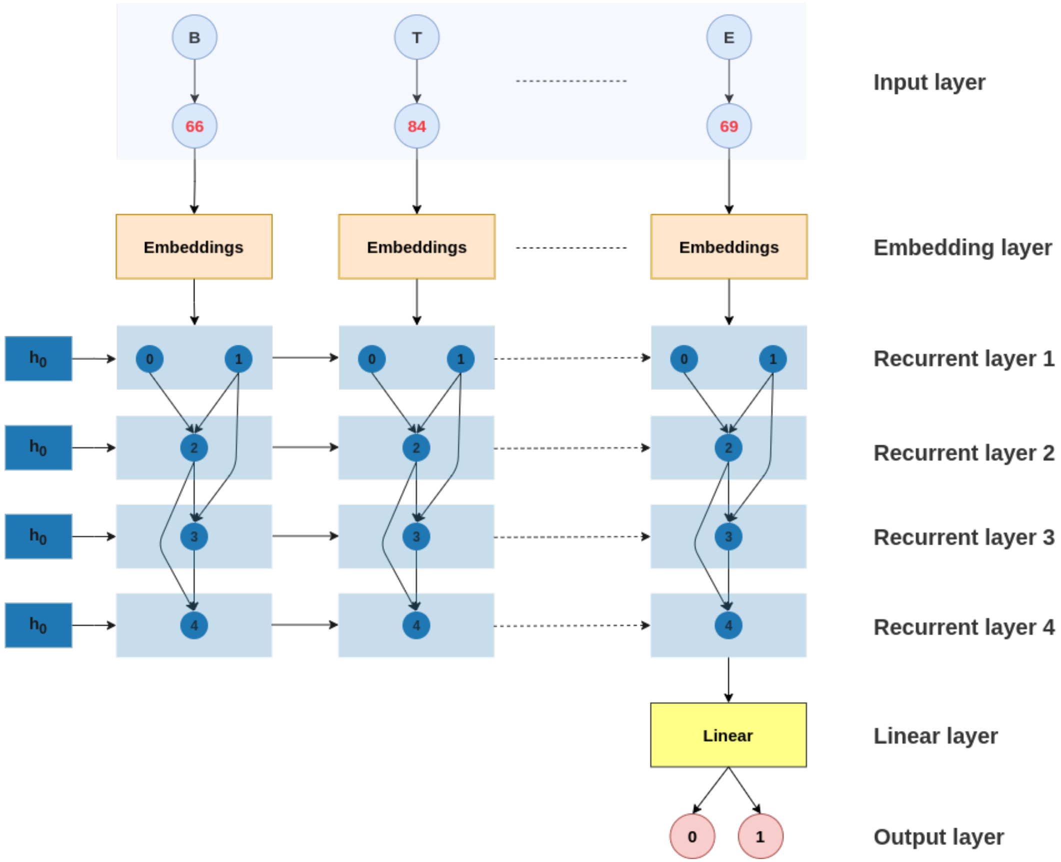
- Using the layer indexing algorithm, compute layer indexing of each node in the random graph.



Layered Random Graph

6.2. RANDOMLY STRUCTURED RNN (cont.)

- Randomly Structured RNN model is then generated by introducing recurrent connections between consecutive layered RG:



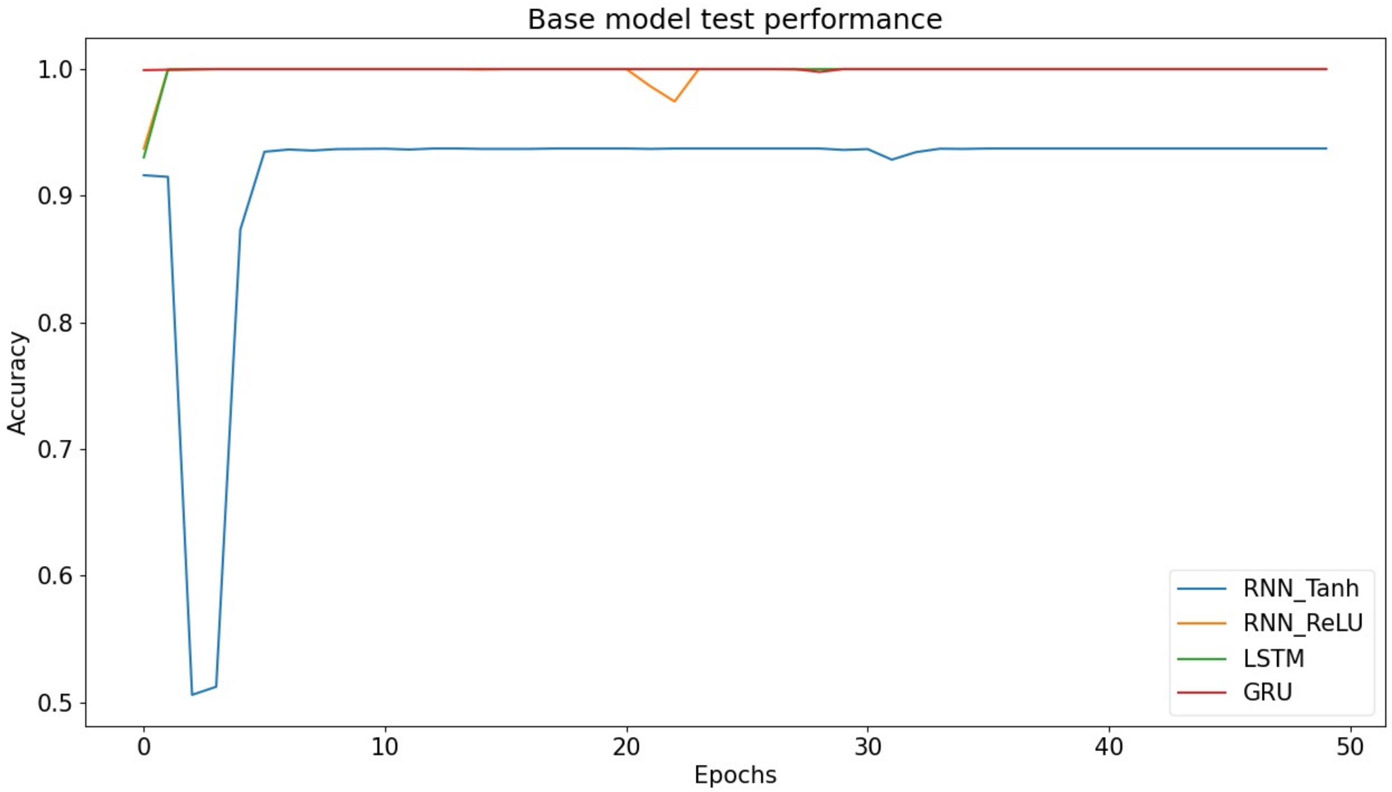
Randomly Structured RNN model

6.3. PERFORMANCE PREDICTION RS RNN

- During training and evaluation of Randomly Structured RNN, graph properties of the base Random Graphs are stored along with its corresponding performance.
- Three regressor algorithms, namely Bayesian Ridge, Random Forest, and AdaBoost, are then trained on this data, with graph properties as features and performance as the target.
- An R^2-value is then reported to understand how these data fit each regressor model.

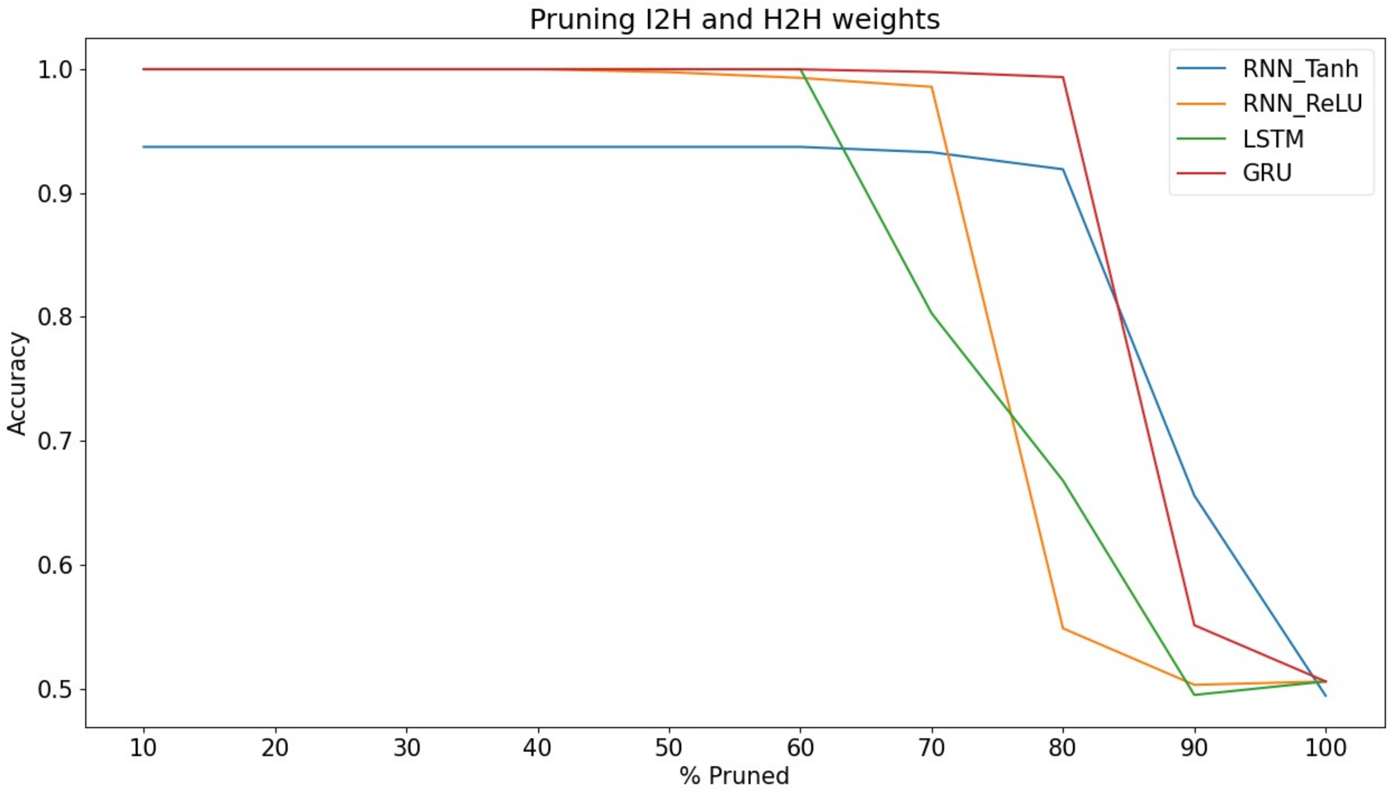
7. RESULTS

- Base model performance:



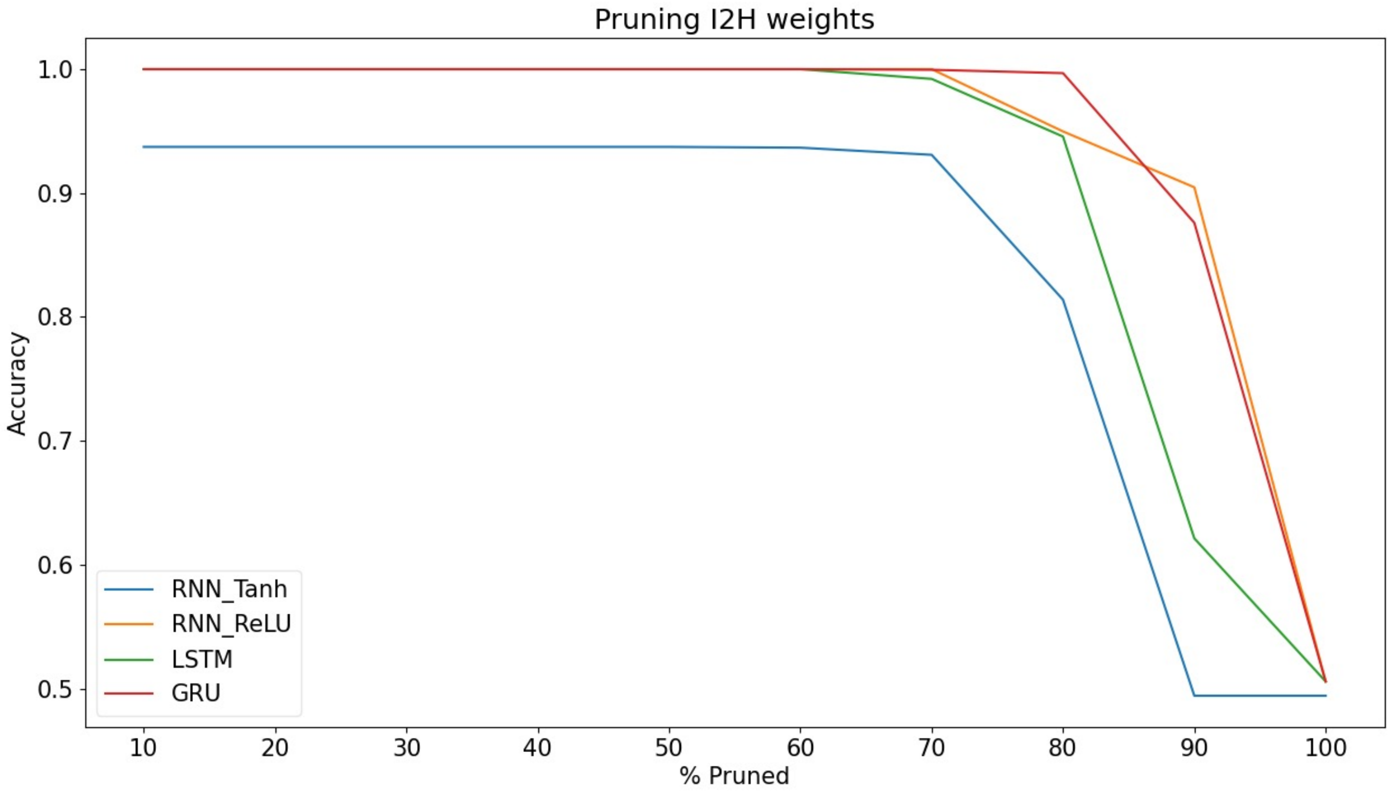
7.1. PRUNING RESULTS

- Pruning performance (*both I2H and H2H*):



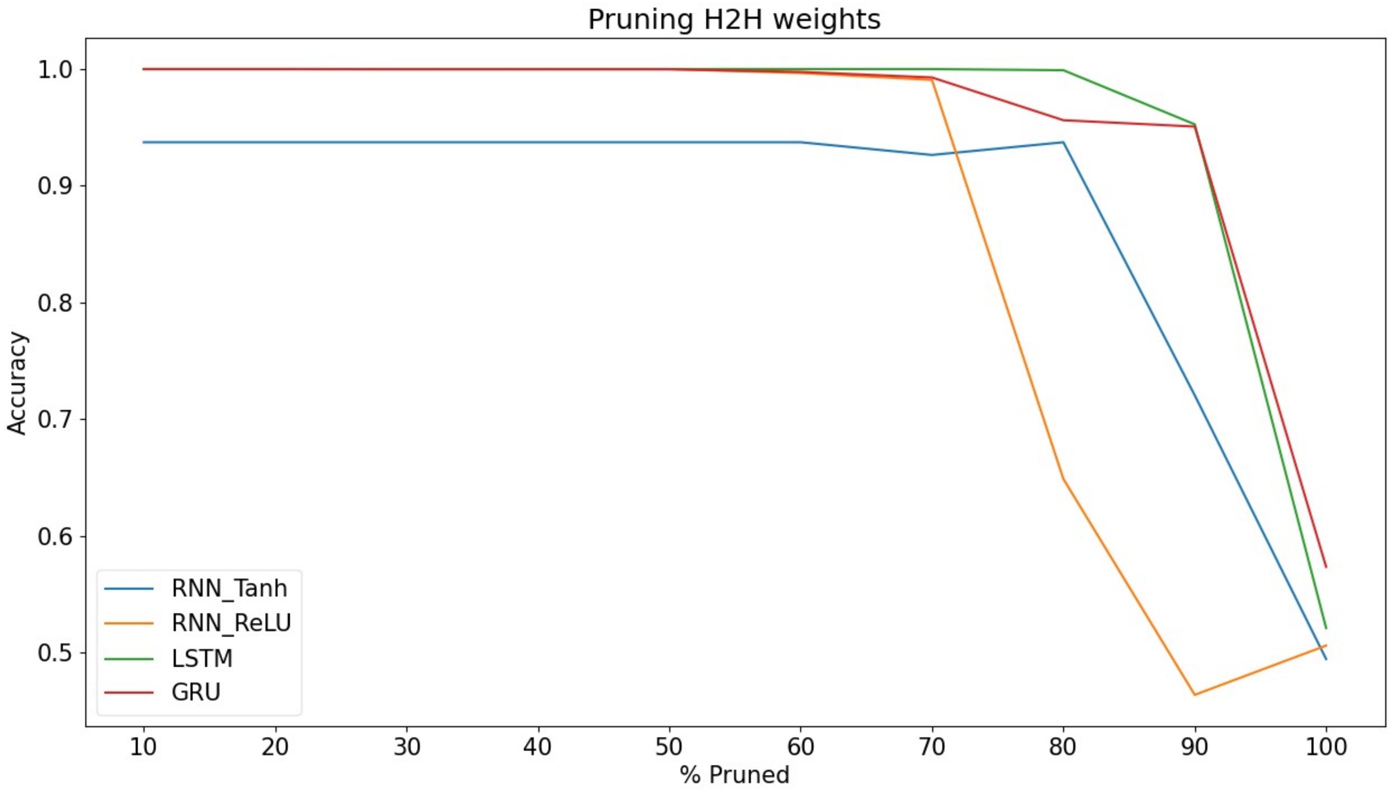
7.1. PRUNING RESULTS (cont.)

- Pruning I2H weights:



7.1. PRUNING RESULTS (cont.)

- Pruning H2H weights:



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7.1. PRUNING RESULTS (cont.)

- In most cases, each pruned model recovers only after one epoch,
  - except in the case of RNN_Tanh, after pruning 90% I2H weights, it requires two epochs to recover.
- In almost all the cases, pruned models never recover after 100% pruning,
  - except in the case of LSTM and GRU, both models still recovers in just one epoch, even with 100% pruning of H2H weights.

7.2. RANDOMLY STRUCTURED RNN PERFORMANCE

Property	Correlation with *test_acc*			
	RNN_Tanh	RNN_ReLU	LSTM	GRU
nodes	**0.40**	**0.44**	**0.44**	**0.49**
edges	0.38	**0.43**	**0.42**	**0.49**
source_nodes	0.35	**0.47**	**0.57**	**0.74**
degree_var	-0.28	-0.26	-0.39	**-0.58**
closeness_var	**-0.46**	-0.39	**-0.51**	**-0.67**
nodes_betweenness_var	**-0.49**	**-0.41**	**-0.56**	**-0.52**
edge_betweenness_var	-0.34	-0.30	**-0.44**	-0.26

Pearson correlation between test accuracy and different graph and recurrent network properties

7.3. PERFORMANCE PREDICTION

RNN variant	Bayesian Ridge	Random Forest	AdaBoost
RNN_Tanh	**0.47919**	0.43163	0.35698
RNN_ReLU	0.36075	**0.61504**	0.53469
LSTM	0.37206	0.57933	**0.59514**
GRU	0.67224	**0.87635**	0.78313

R^2-value from each regressor, for each RNN variant

8. CONCLUSION

- Two different methods to induce sparsity:
  1. Pruning,
  2. Randomly structured RNN
- Pruning results conclude that the weight complexity of various RNN variants can safely be reduced by more than 60%.
- In most cases of pruning, it only takes one epoch for a model to recover.
- Random structure experiments identified two essential graph properties that are mutual in all four RNN variant.
- Performance prediction experiment shows data from RNN_ReLU and GRU fits well with Random Forest, while the data from LSTM fits good with AdaBoost.

THANK YOU

QUESTIONS?