An Incremental Encoder For Sequence-to-Sequence Modelling

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What is incrementality?

(and why do we care)

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→ “Incrementally integrating information”

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- Attention-based models are not biologically plausible; don’t give incentive to encode efficiently

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How to measure incrementality?

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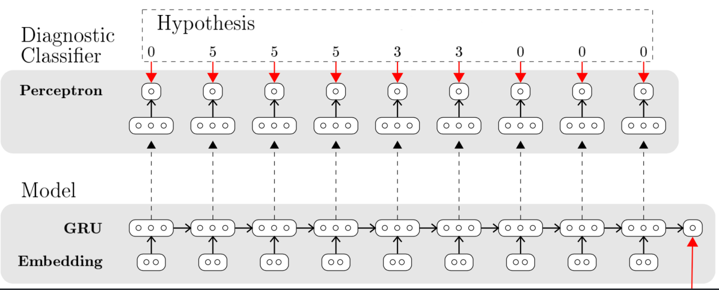
3. Do representations for the same type resemble each other?

1. How well / long is past information stored?

- Use *Diagnostic Classifiers* (Hupkes et al., 2018)



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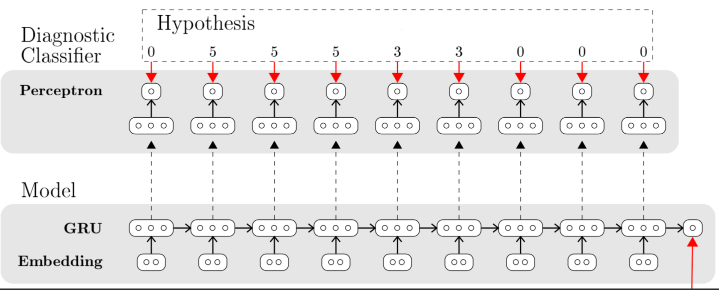
  - Use hidden activations as input for a simple Perceptron, try to predict some information



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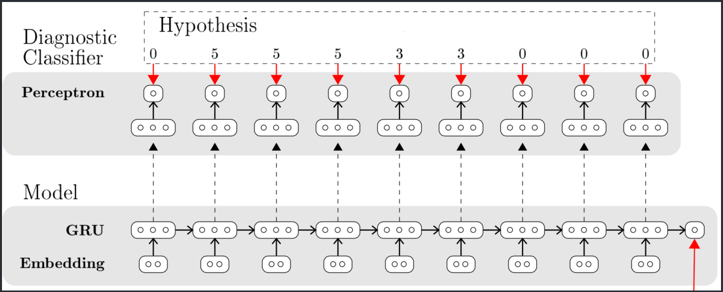
  → High Accuracy = Information is likely being stored



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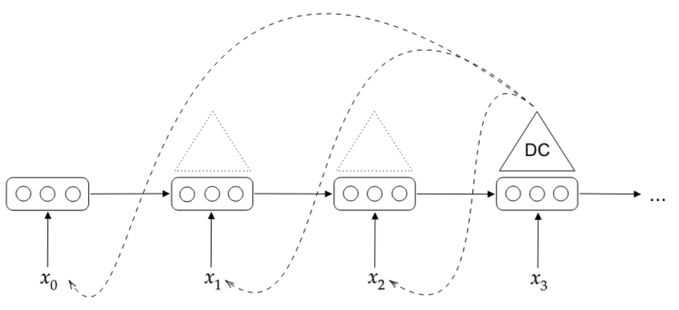

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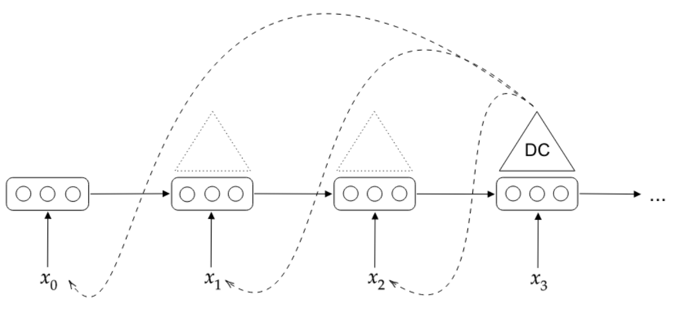
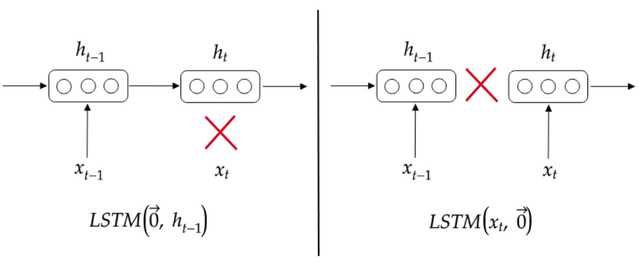


- Average Diagnostic Classifier Accuracy
  - Use activations h_t to predict the occurrence of token $x_{t'}$
- Weighed Average Diagnostic Classifier Accuracy
  - Weigh by distance $t - t'$

2. How much new information is integrated?

- If no new information is integrated, then $||h_t - \mathrm{LSTM}(\vec{0}, h_{t-1})|| = 0$



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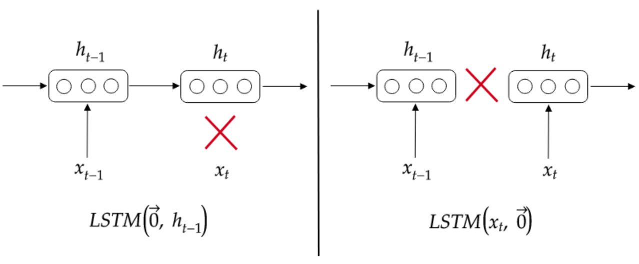

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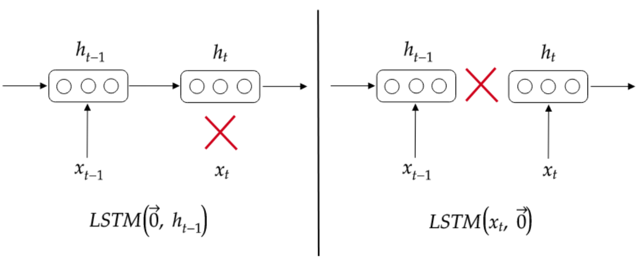
- Hypothesis: Incremental model finds trade-off between old and new information



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→ Integration Ratio

$$\phi = \frac{||h_t - \mathrm{LSTM}(\vec{0}, h_{t-1})||}{||h_t - \mathrm{LSTM}(x_t, \vec{0})||} \tag{1}$$

$$\mathrm{intratio}(\{x\}_0^T) = \frac{1}{T}\sum_{t=1}^{T} \min\left(\phi, \phi^{-1}\right) \tag{2}$$

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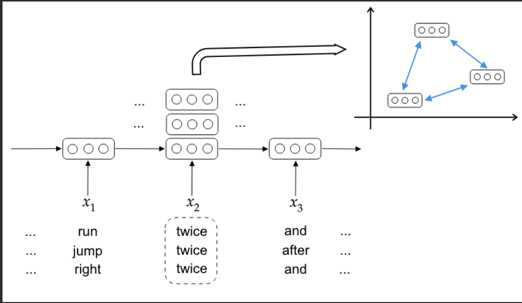
- We expect representations to be **close** in hidden space when encoding the **same type**
- Representational similarity
  - Calculate average euclidean distance between h_t for same x_t



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Standard models

- Vanilla LSTM
- LSTM with dot-product attention

An incremental (?) model

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→ Add a secondary Anticipation Loss to training
  - Project hidden representations into vocabulary space, use cross-entropy loss to compare with actual next token

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Dataset

- Use the SCAN (Lake and Baroni, 2018) data set
  - Translate commands in Natural Language into sequence of commands

    jump thrice and look ⟶ `I_JUMP I_JUMP I_JUMP I_LOOK`

  - Designed to test compositionality

Setup

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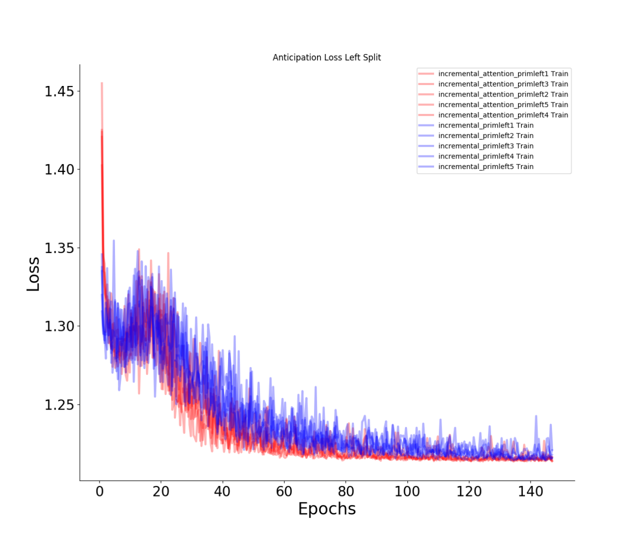
  $\longrightarrow$ Measure correlation!

Results

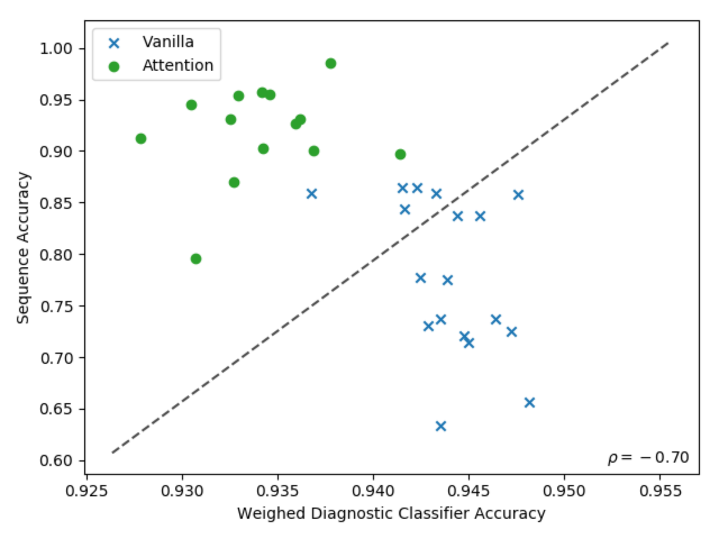
Model	seq_acc	dc_acc	wdc_acc	intratio	repsim
BL	$.765 \pm .07$	$.958 \pm 0$	$.945 \pm 0$	$\mathbf{.714 \pm .02}$	$4.399 \pm .08$
BL + Attn.	$\mathbf{.919 \pm .05}$	$.950 \pm 0$	$.935 \pm 0$	$.697 \pm .01$	$\mathbf{3.859 \pm .08}$
Antcp. Loss	$.661 \pm .23$	$.957 \pm 0$	$.943 \pm 0$	$.664 \pm .02$	$\mathbf{3.834 \pm .11}$

Figure: Results on SCAN `add_prim_left` with $n = 15$.

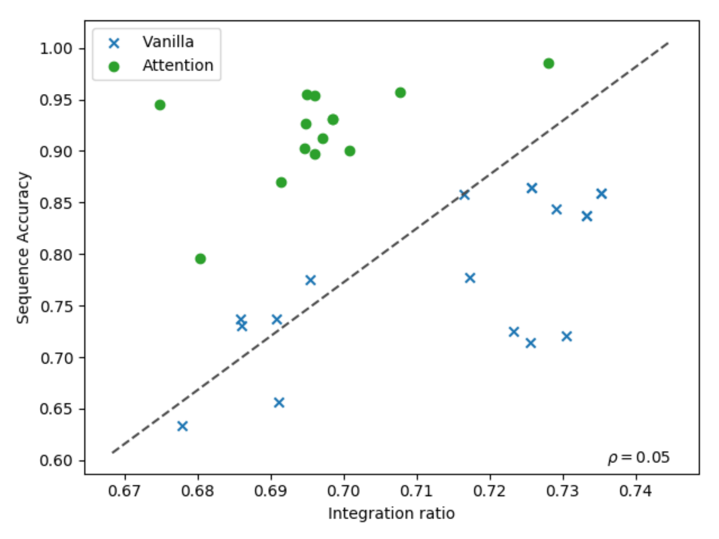
Anticipation Loss insights



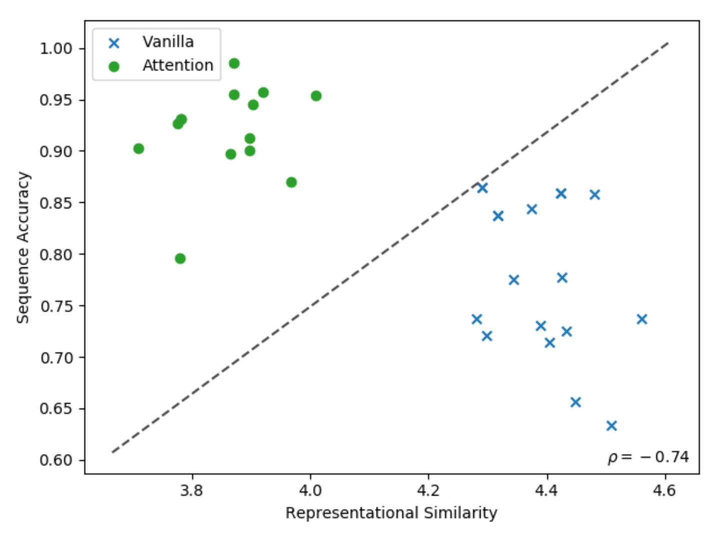
Metrics Insights I



Metrics Insights II



Metrics Insights III



Metrics Insights IV

	seq_acc	dc_acc	wdc_acc	intratio	repsim
seq_acc	1	−0.80	−0.79	0.05	−0.74
dc_acc		1	0.78	0.29	**0.81**
wdc_acc			1	0.40	**0.80**
intratio				1	0.39
repsim					1

Figure: Correlation between metrics measured with Pearson's ρ.

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- How to realize insights about human cognition in model architectures?

Future Work

- Improving metrics

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- Models based on *Chunk-and-Pass processing*

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- Your ideas?

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- Improving metrics
- Models based on *Chunk-and-Pass processing*
- Your ideas?
- Master thesis: Activation interventions

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