Recurrent Neural Networks, I

LING 574 Deep Learning for NLP
Shane Steinert-Threlkeld

Today's Plan

- Last time:
  - Computation graphs + backpropagation
  - Deep Averaging Network (DAN)
- Quick notes on edugrad
- Neural Probabilistic Language Model (feed-forward model)
- Additional Training Notes
  - Regularization
  - Early stopping
  - Hyper-parameter searching
- Intro to *Recurrent* Neural Networks

Announcements

- HW2 reference code now available
- Tests: hwX/test_all.py. NB: necessary, but not sufficient, to check correctness of your code. From command-line, run `pytest` from your HW directory, with environment activated.
- Implementing ops in edugrad:
  - You can use any numpy operations you want; goal is to understand forward/backward API
  - https://github.com/shanest/edugrad
  - Log: base e, don't need to do special handling of bad input arguments (like 0)
- Edugrad is installed in the course conda environment, so be sure to activate it

Decorators

- @tensor_op in edugrad code: what is this??
  - This converts \`Operation\`s into methods on \`Tensor\`s
  - Handles dynamic graph construction, the \`ctx\` magic, etc.
- Python decorator (similar to decorator design pattern)
  - Design pattern to extend an object with more functionality
  - Decorators *wrap* their arguments, add features
    - e.g. registering in a central DB
- In python, syntactic sugar:
  - With more complicated use cases
- Canonical examples: @classmethod, @staticmethod

```
@my_decorator
def fn(...):


def fn(...):

fn = my_decorator(fn)
```

Decorator Demo

```python
def printer(method, *args):
    def fn(*args):
        output = method(*args)
        print(f"Output: {output}")
    return fn

@printer
def add(a, b):
    return a + b

add(1, 2) # prints "Output: 3"
```

Recurrent Neural Networks

RNNs: high-level

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  - Previous classifier: average embeddings of words
  - Previous LM: *n*-gram assumption (i.e. fixed-size context of word embeddings)

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  - Maintaining “hidden” state
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- RNNs process *sequences* of vectors
  - Maintaining “hidden” state
  - Applying the same operation at each step
- Different RNNs:
  - Different operations at each step
  - Operation also called “recurrent cell”
  - Other architectural considerations (e.g. depth; bidirectionally)

Long-distance dependencies, I: number

- Language modeling (fill-in-the-blank)
  - The keys ____
  - The keys on the table ____
  - The keys next to the book on top of the table ____
- To get the number on the verb, need to look at the subject, which can be very far away
  - And number can disagree with linearly-close nouns

Selectional Restrictions

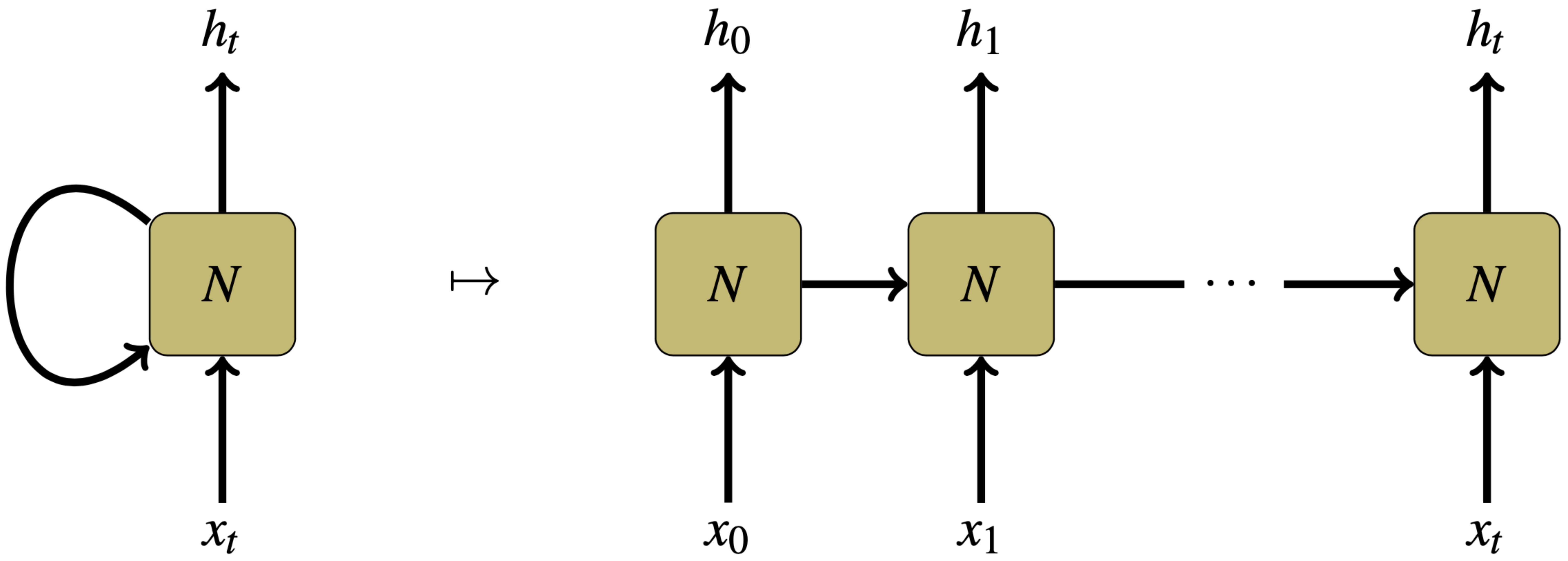
- The **family** moved from the city because they wanted a larger ____.
- The **team** moved from the city because they wanted a larger ____.

Selectional Restrictions

- The **family** moved from the city because they wanted a larger **house**.
- The **team** moved from the city because they wanted a larger **market**.

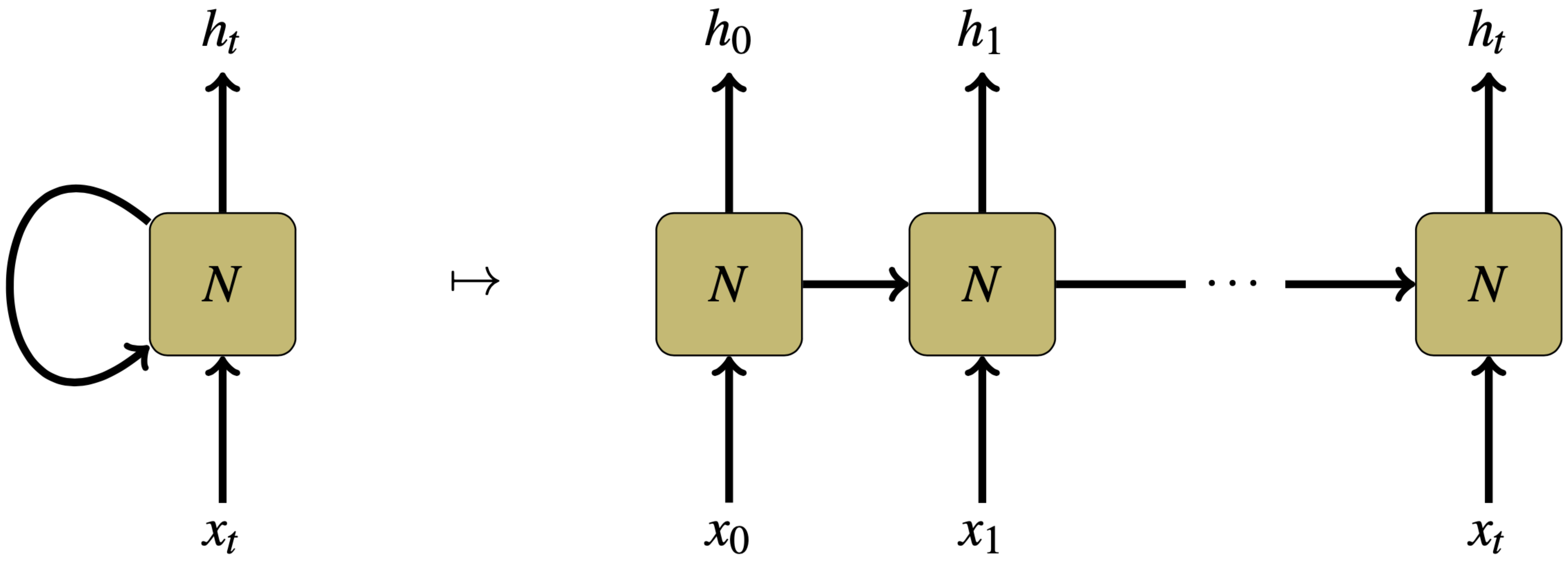
- Need models that can capture long-range dependencies like this.
- N-gram (whether count-based or neural) cannot. E.g., with n=4:
  - P(word | "they wanted a larger")

RNNs



Steinert-Threlkeld and Szymanik 2019; Olah 2015

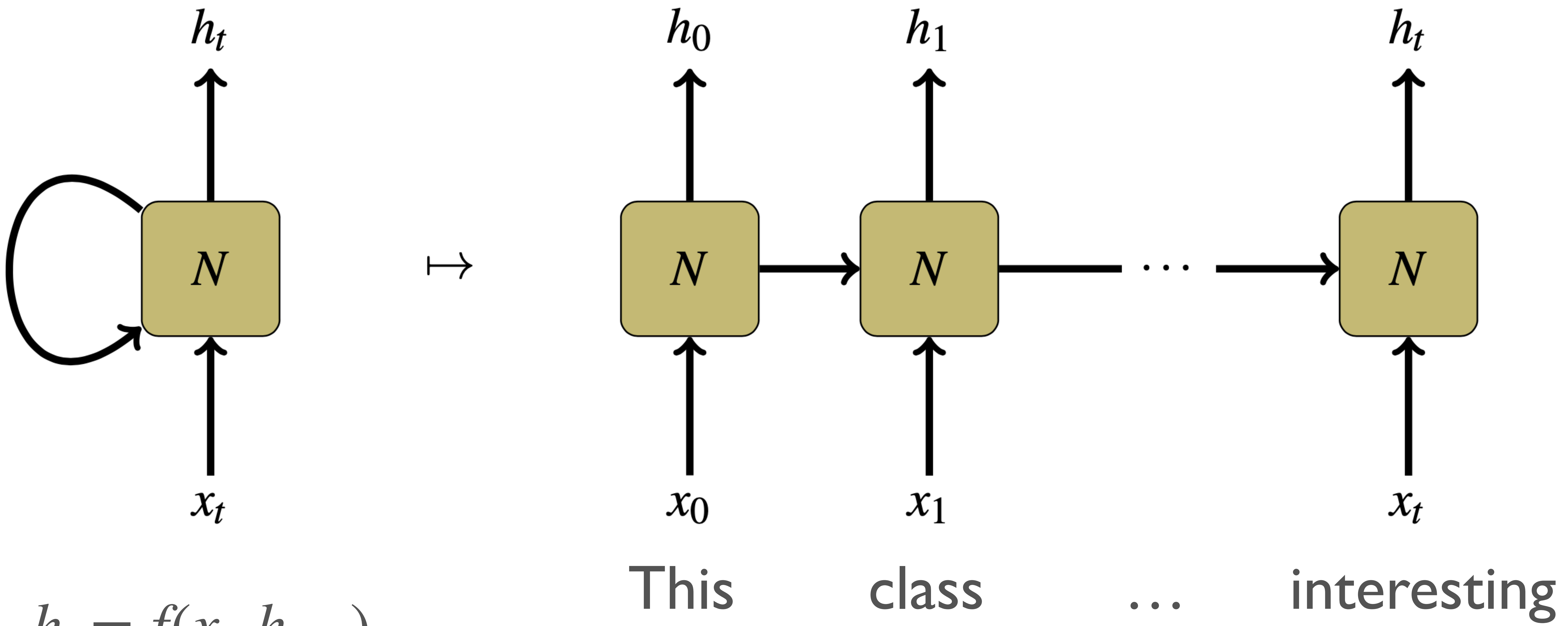
RNNs



$$h_t = f(x_t, h_{t-1})$$

[Steinert-Threlkeld and Szymanik 2019](); [Olah 2015]()

RNNs



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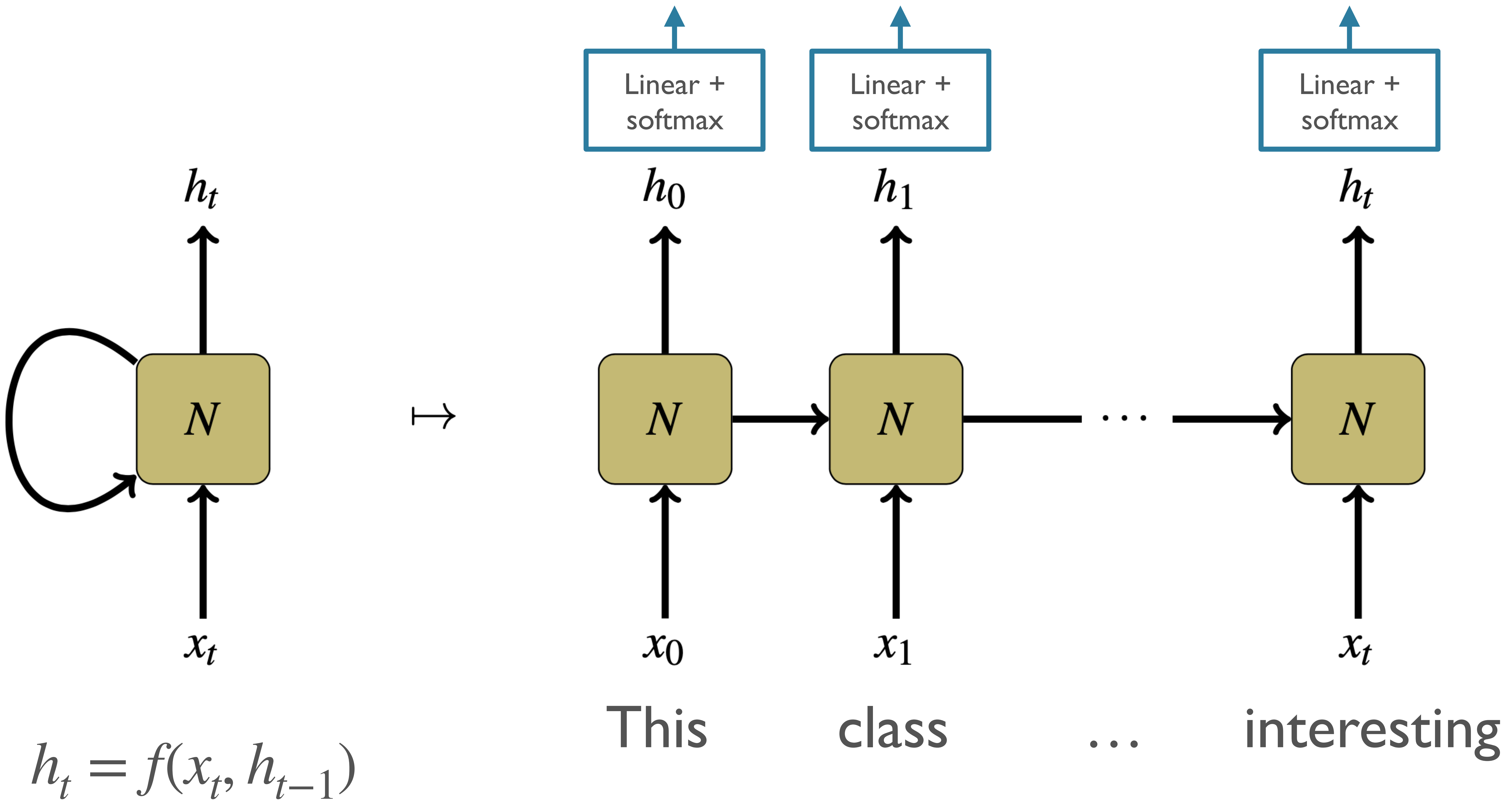

Steinert-Threlkeld and Szymanik 2019; Olah 2015

Simple / Vanilla / Elman RNNs

- Same kind of feed-forward computation we've been studying, but:
  - x_t: sequence element at time *t*
  - h_{t-1}: hidden state *of the model* at previous time *t-1*

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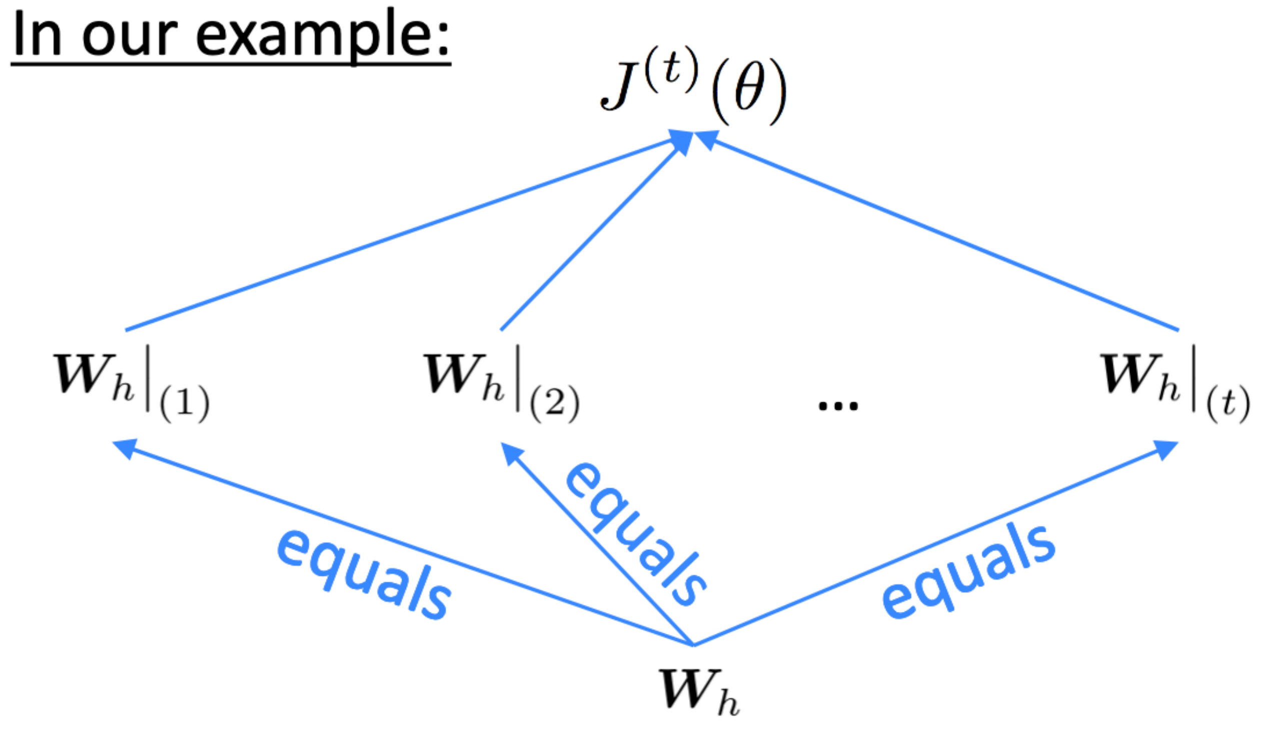
Simple/"Vanilla" RNN: $$h_t = \tanh(x_t W_x + h_{t-1} W_h + b)$$

Training: BPTT

- Backpropagation Through Time
- “Unroll” the network across time-steps
- Apply backprop to the “wide” network
  - Each cell has the *same* parameters
  - Gradients sum across time-steps
    - Multi-variable chain rule

In our example:



Apply the multivariable chain rule:

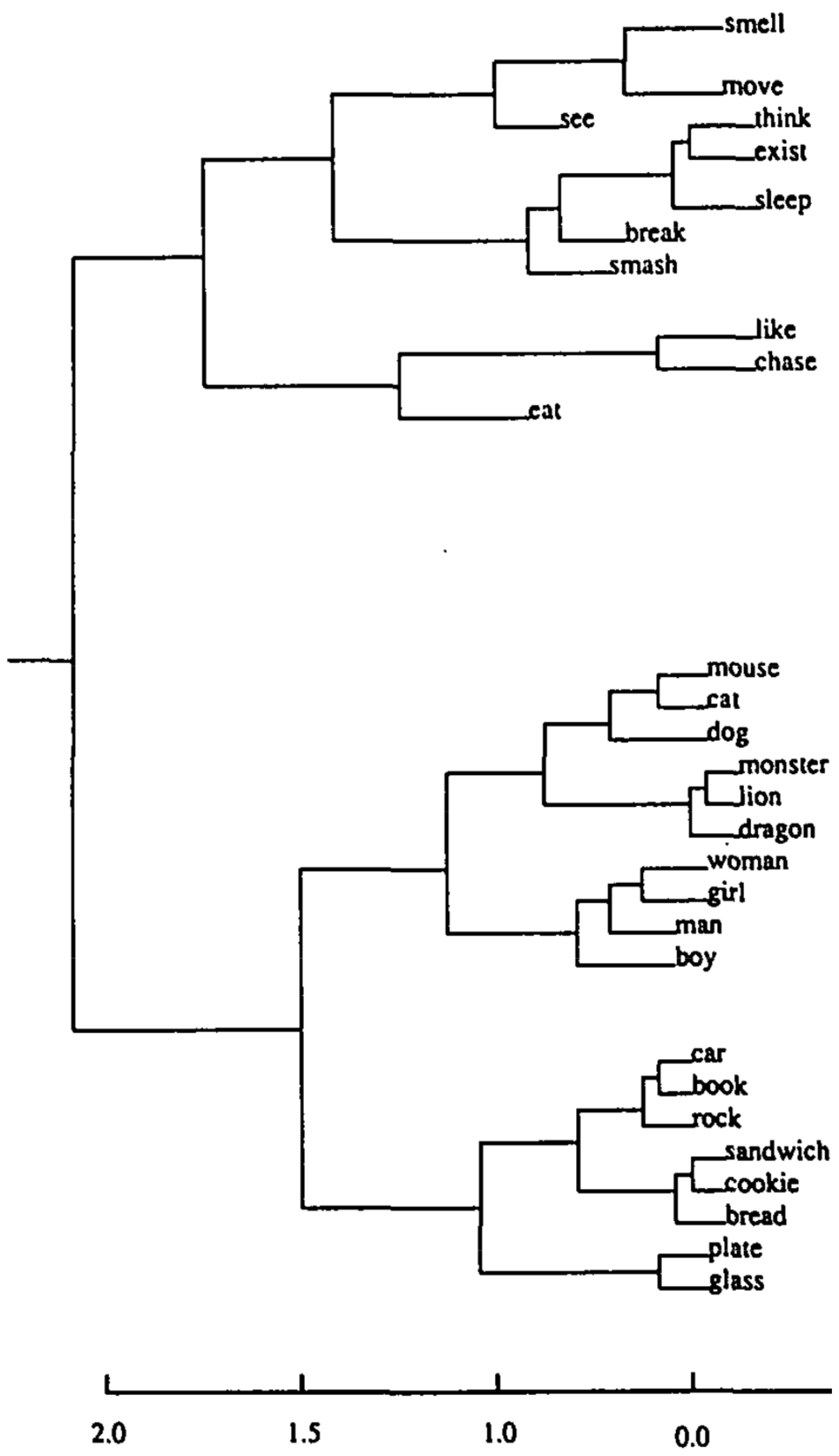
$$\frac{\partial J^{(t)}}{\partial \boldsymbol{W}_h} = \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial \boldsymbol{W}_h}\bigg|_{(i)} \overset{=1}{\boxed{\frac{\partial \boldsymbol{W}_h|_{(i)}}{\partial \boldsymbol{W}_h}}}$$

$$= \sum_{i=1}^{t} \frac{\partial J^{(t)}}{\partial \boldsymbol{W}_h}\bigg|_{(i)}$$

source

Power of RNNs

Hierarchical clustering of Vanilla RNN hidden states trained as LM on synthetic data:



What trends do you notice?

[Elman 1990]

Power of RNNs

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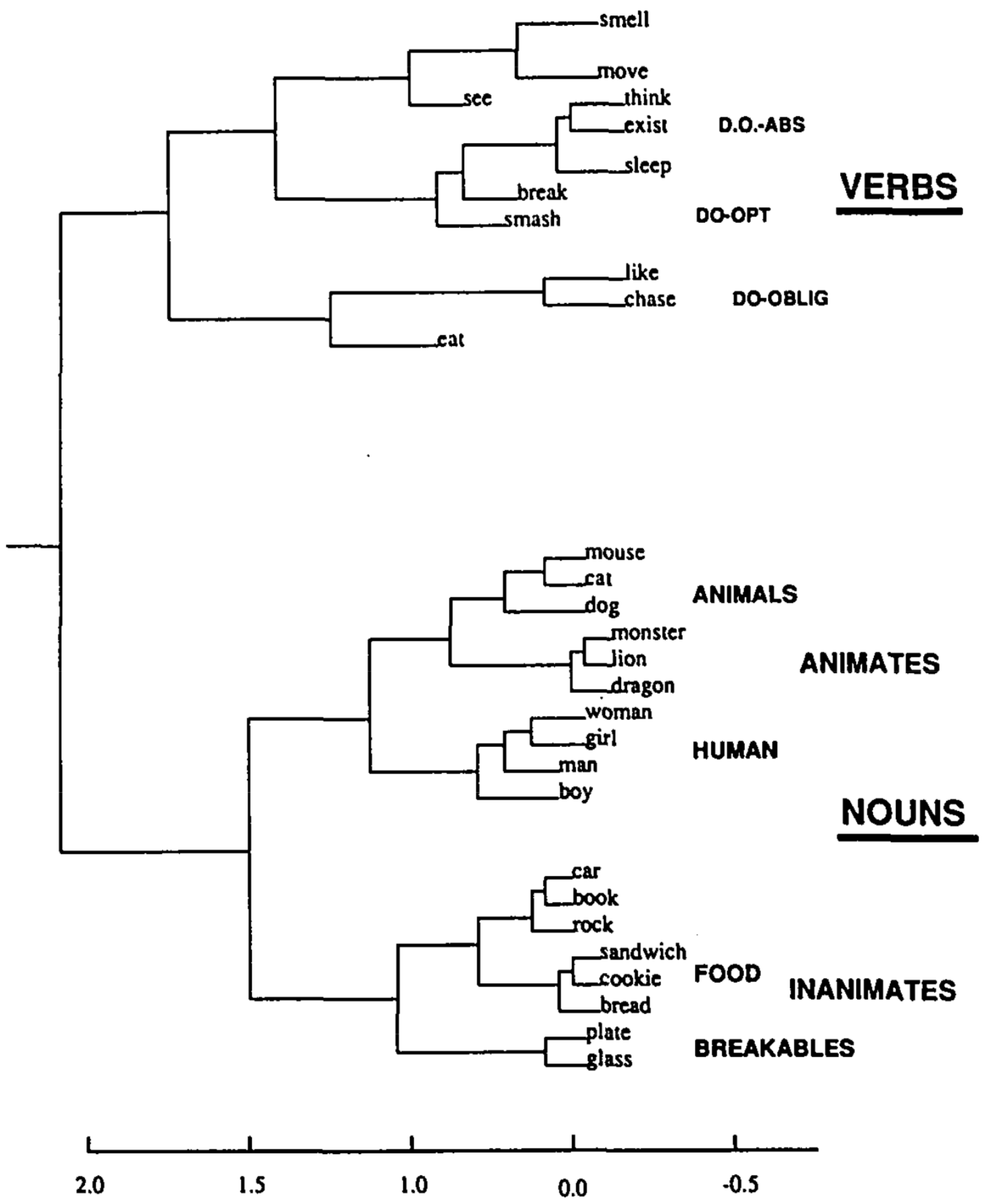
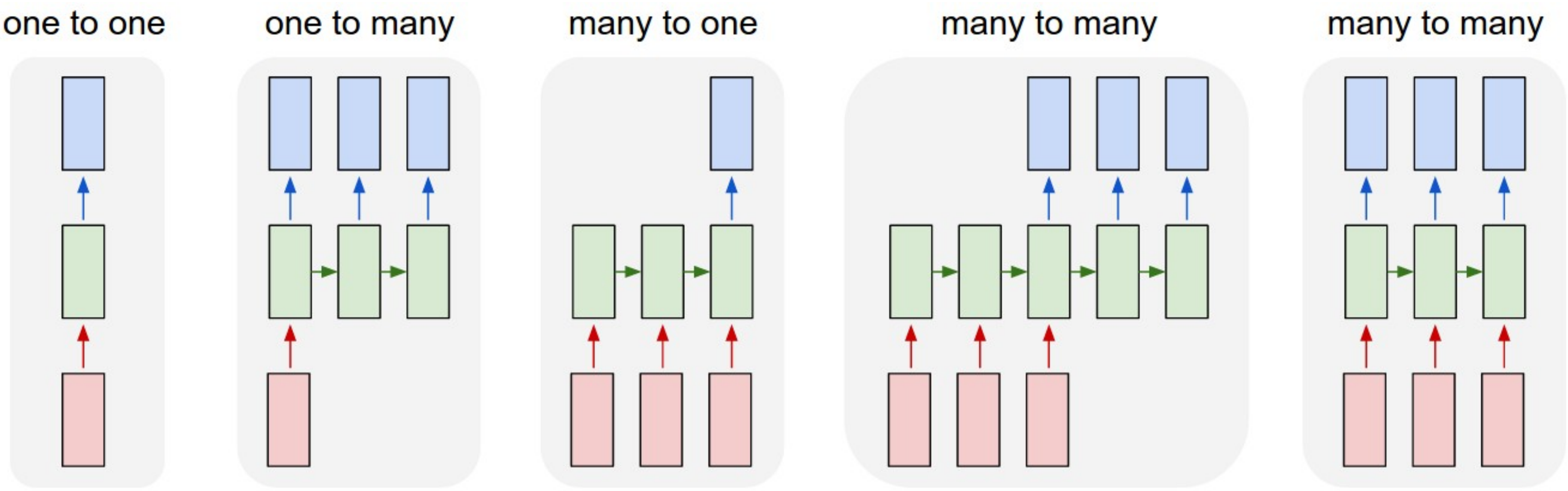


Elman 1990

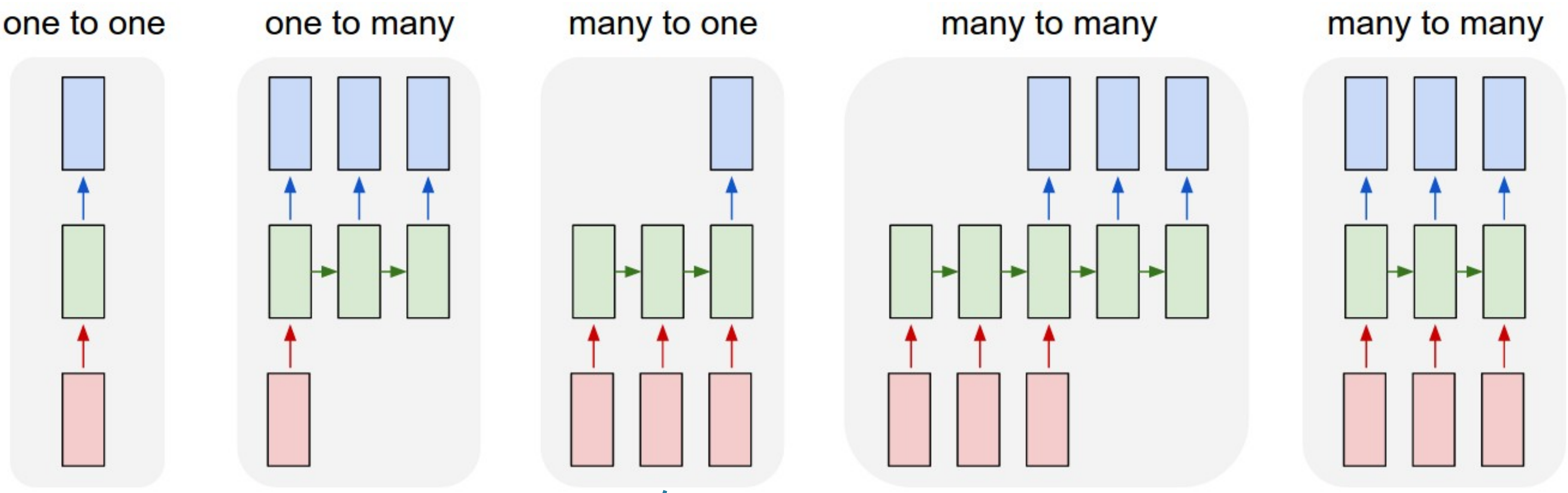
Using RNNs



MLP

e.g. image captioning

Using RNNs

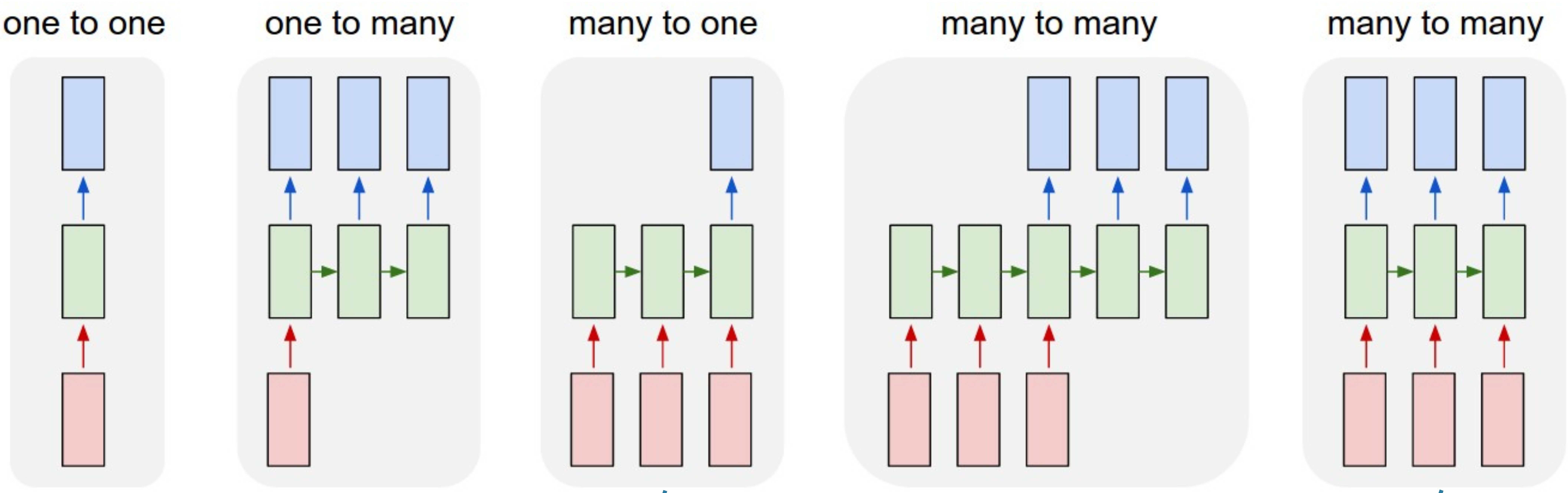


MLP

e.g. image captioning

e.g. text classification

Using RNNs



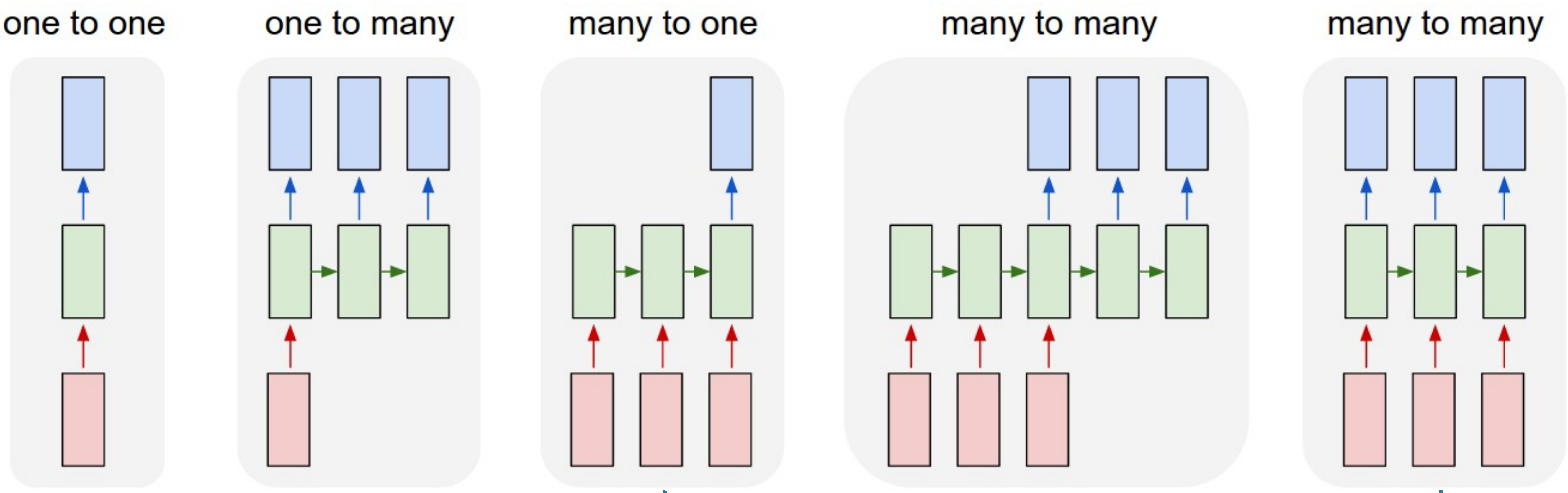
MLP

e.g. image captioning

e.g. text classification

e.g. POS tagging

Using RNNs



MLP

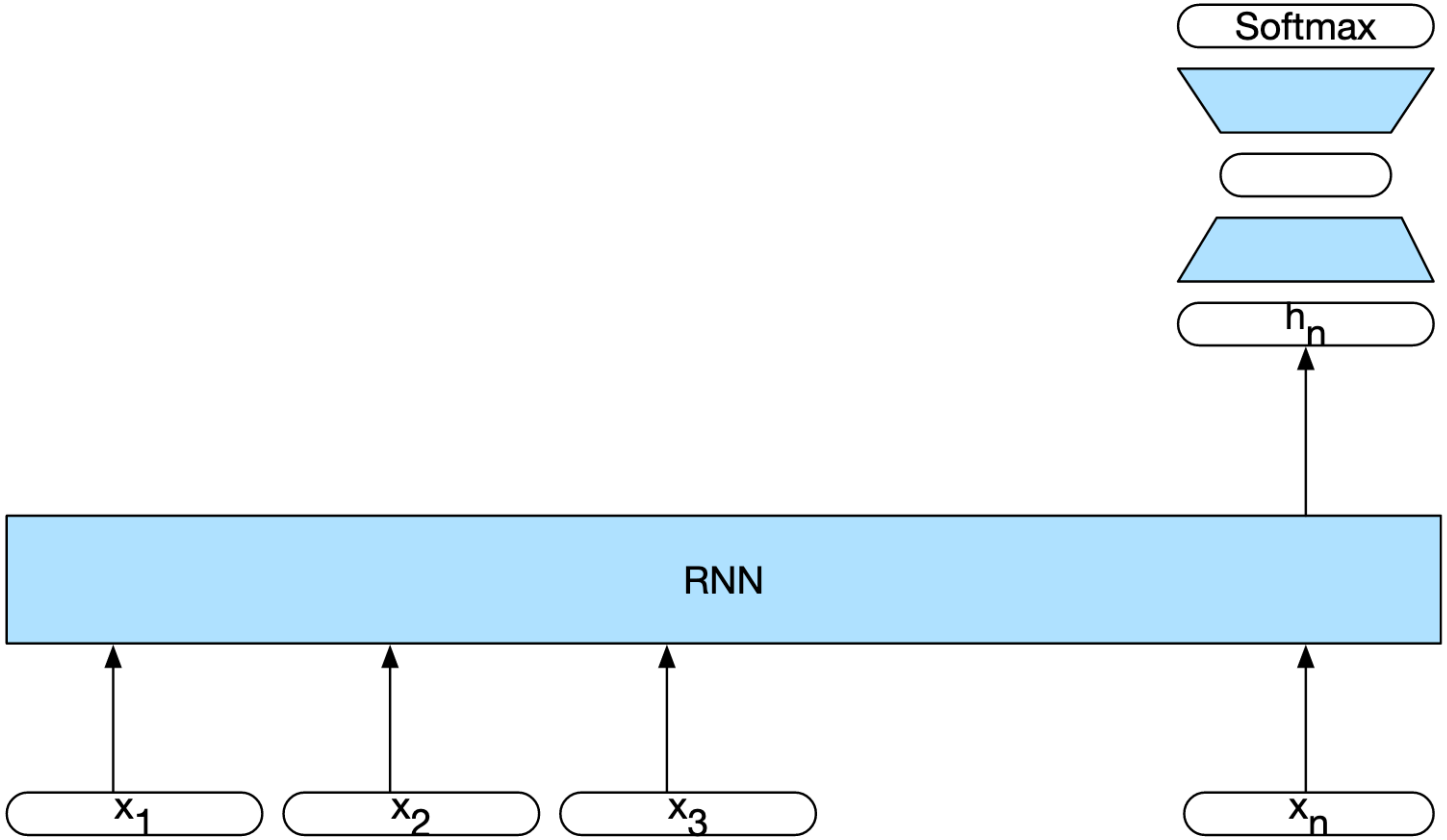
e.g. image captioning

seq2seq (later)

e.g. text classification

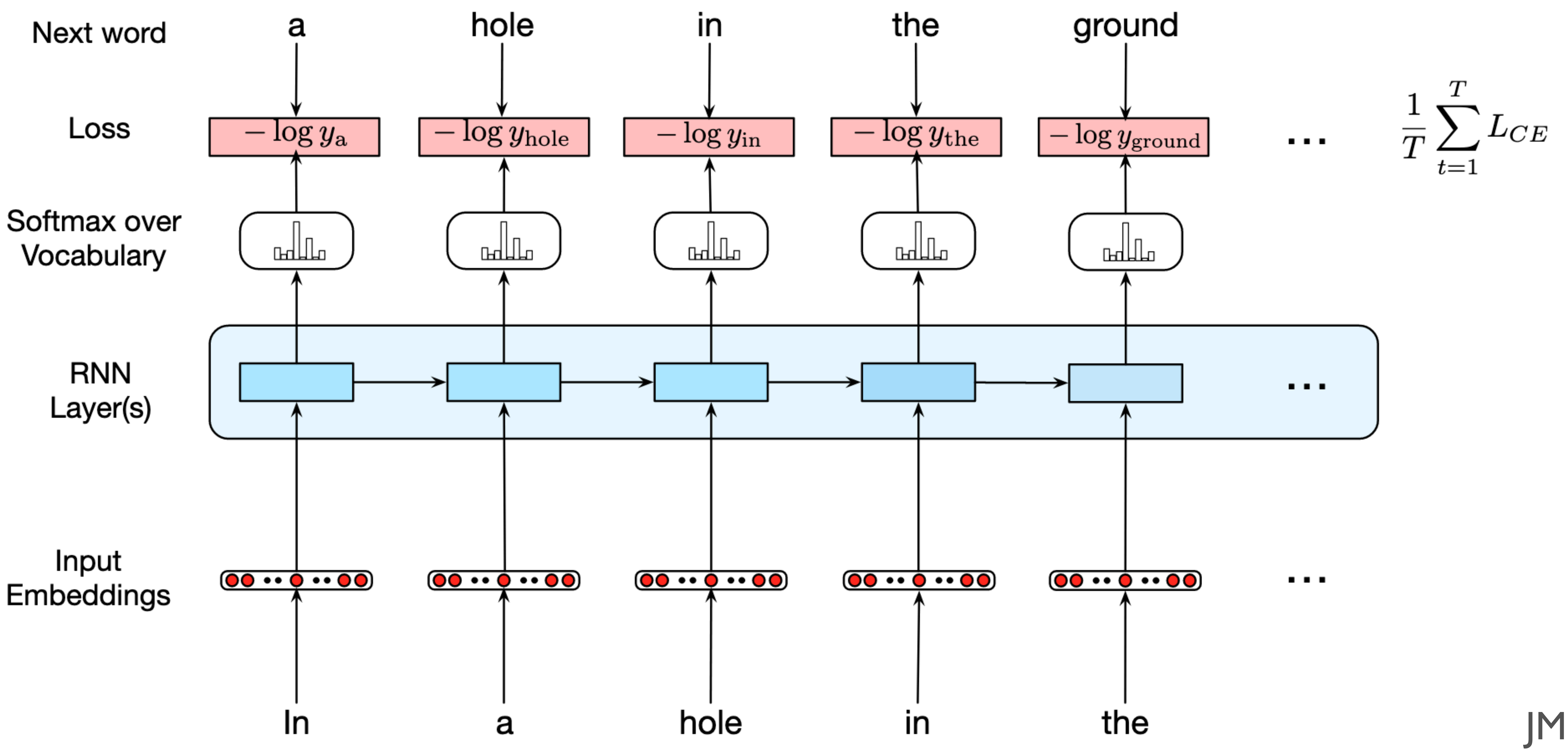
e.g. POS tagging

RNN for Text Classification



JM sec 9.2.5

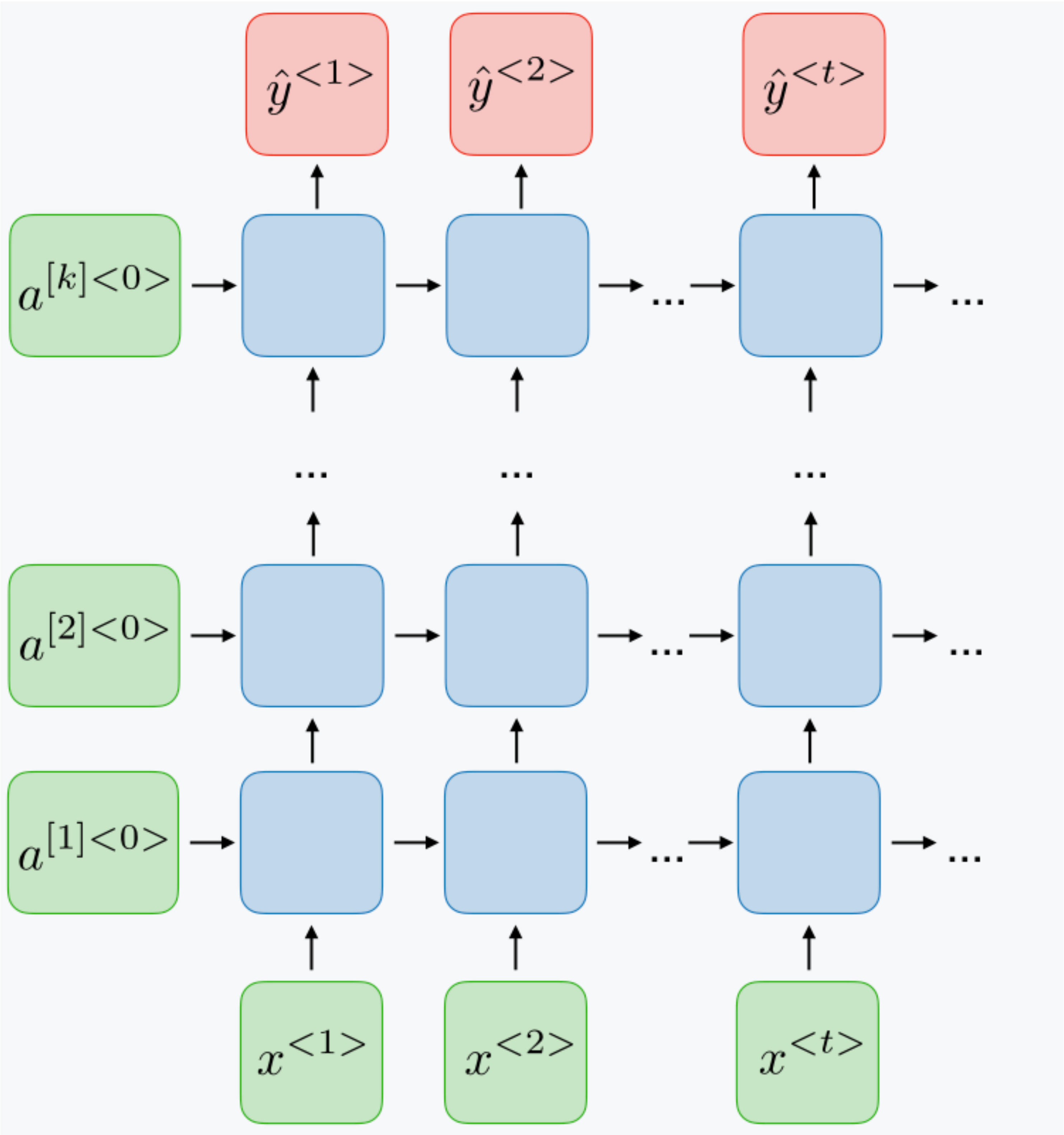
RNNs for Language Modeling



JM sec 9.2.3

Two Extensions

- Deep RNNs:



Source: RNN cheat sheet

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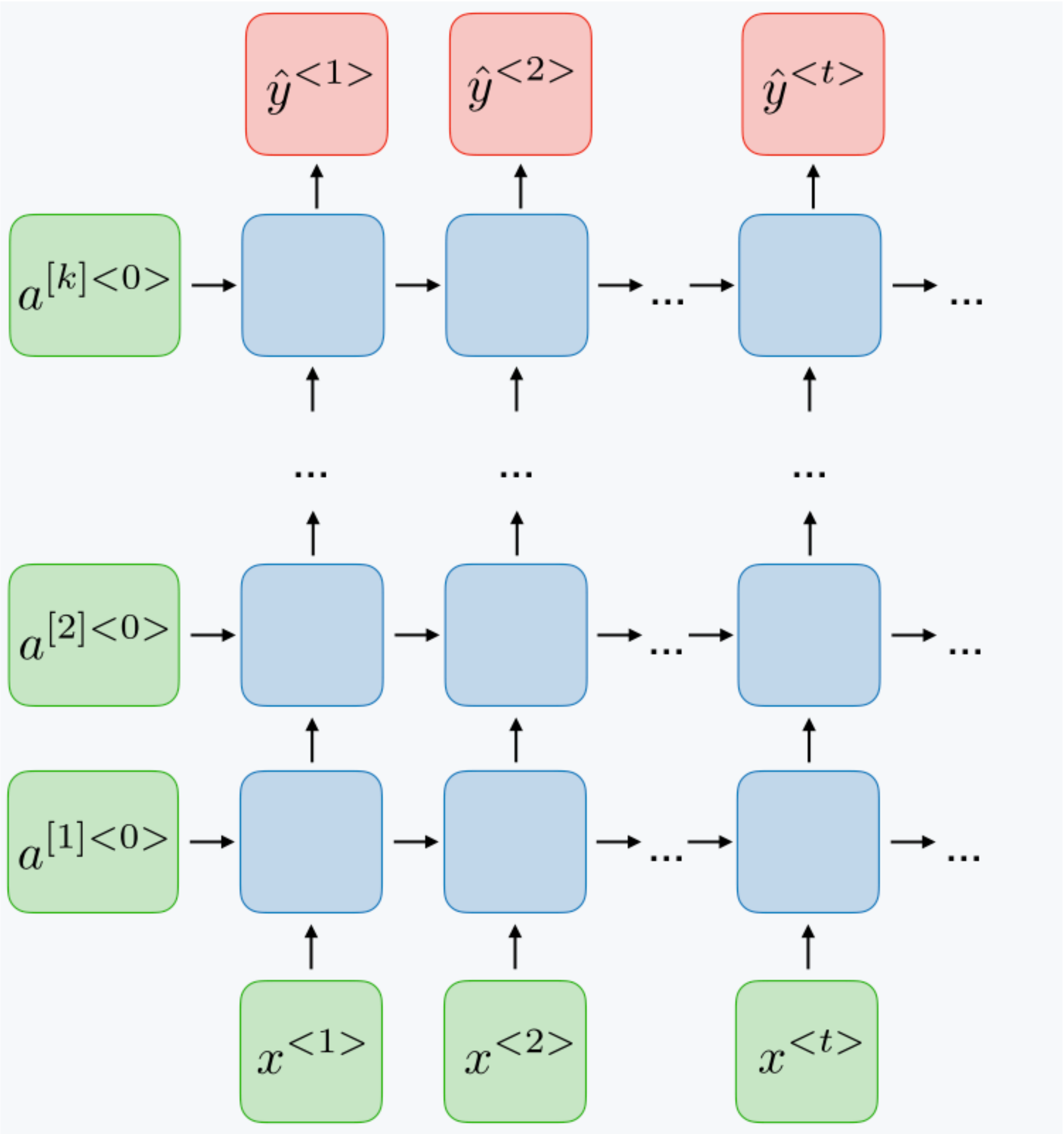
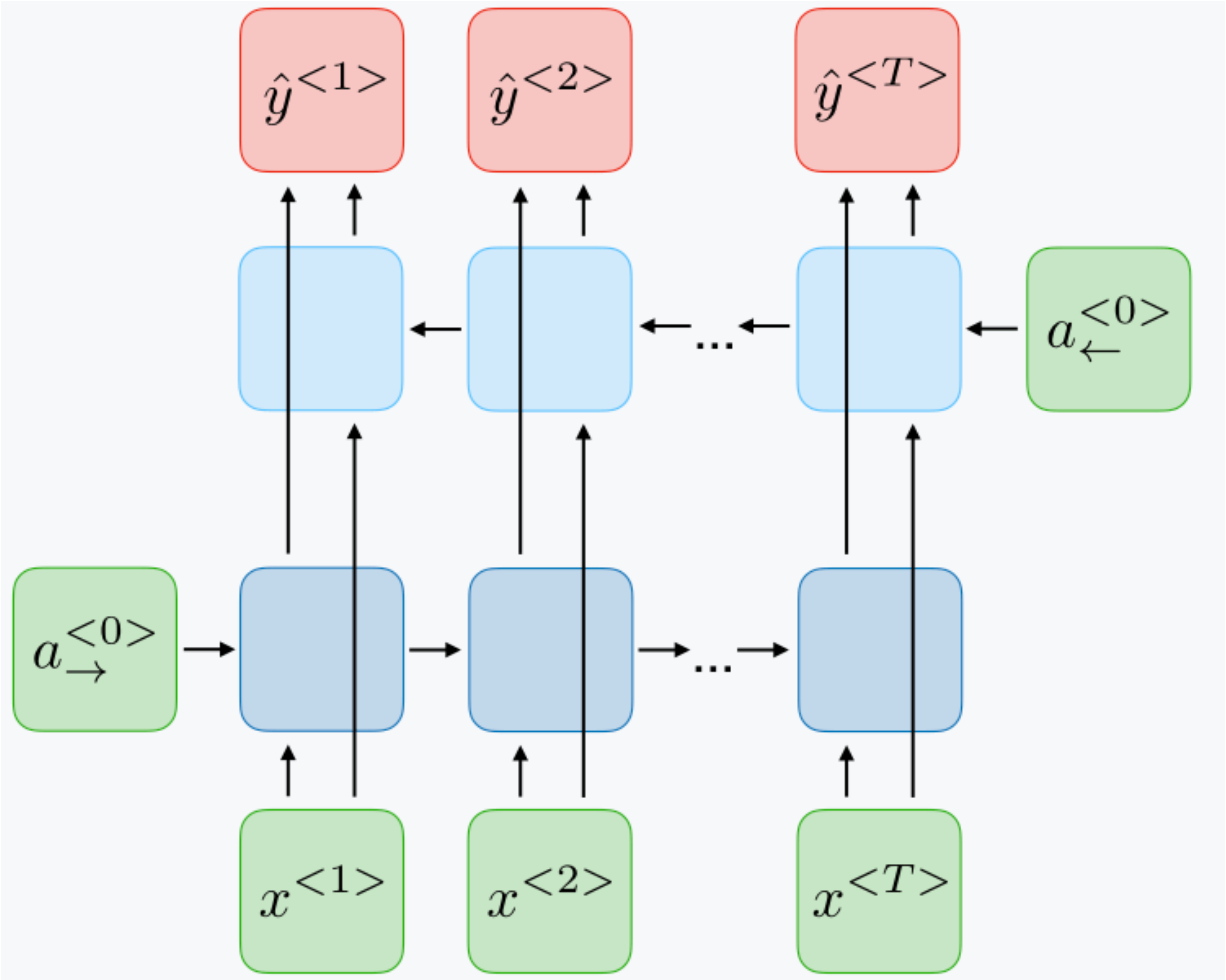


- Bidirectional RNNs:



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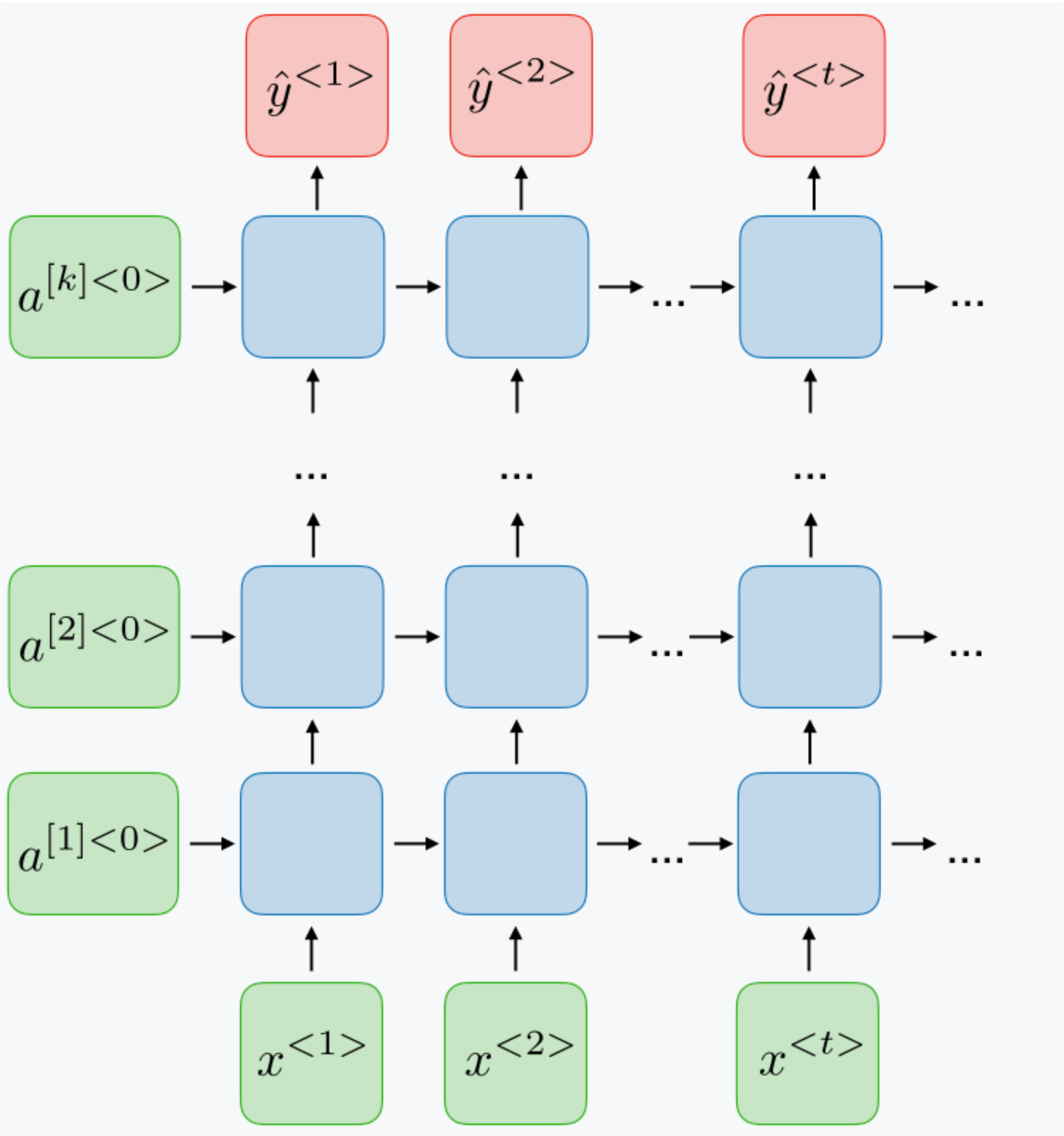

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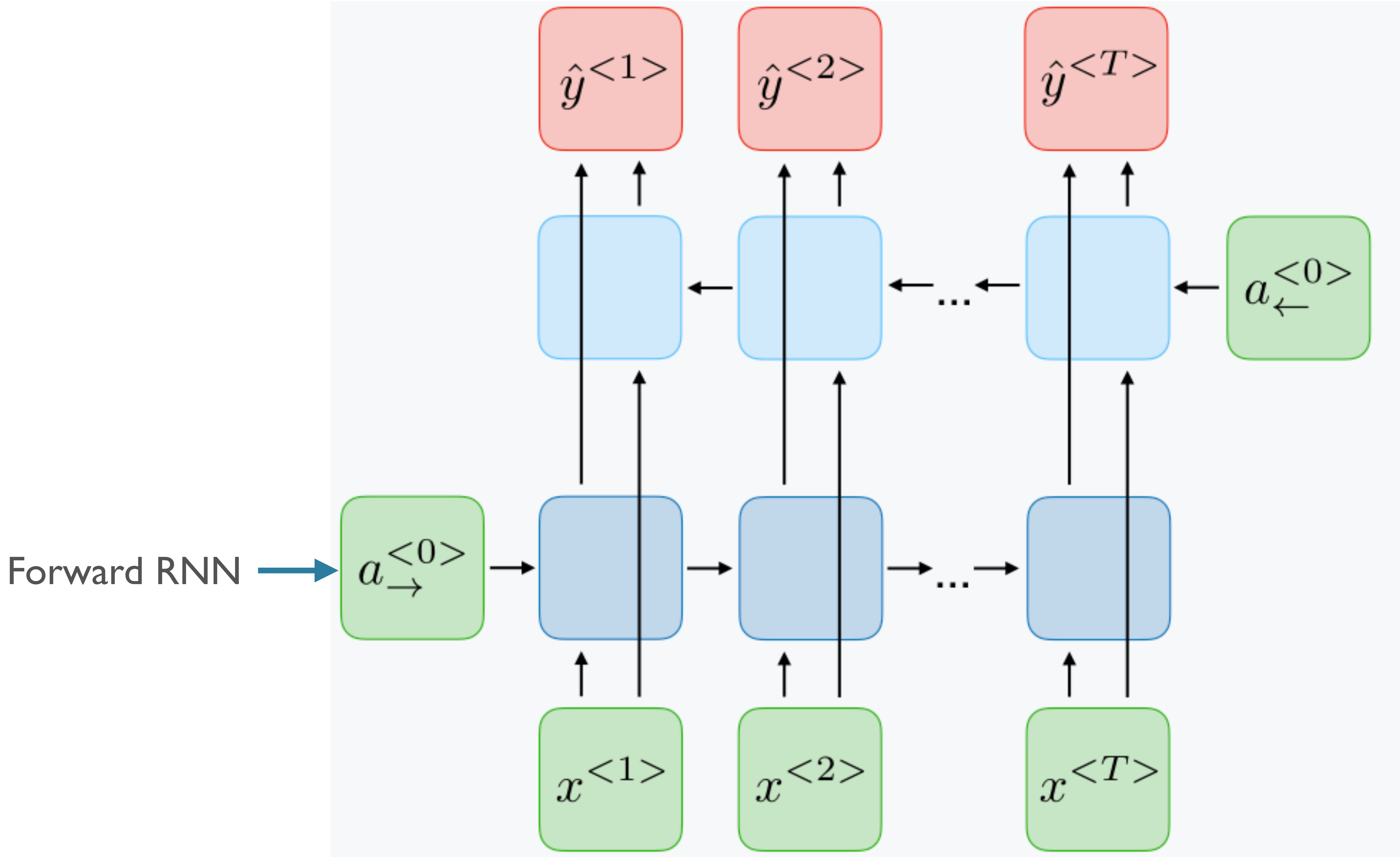

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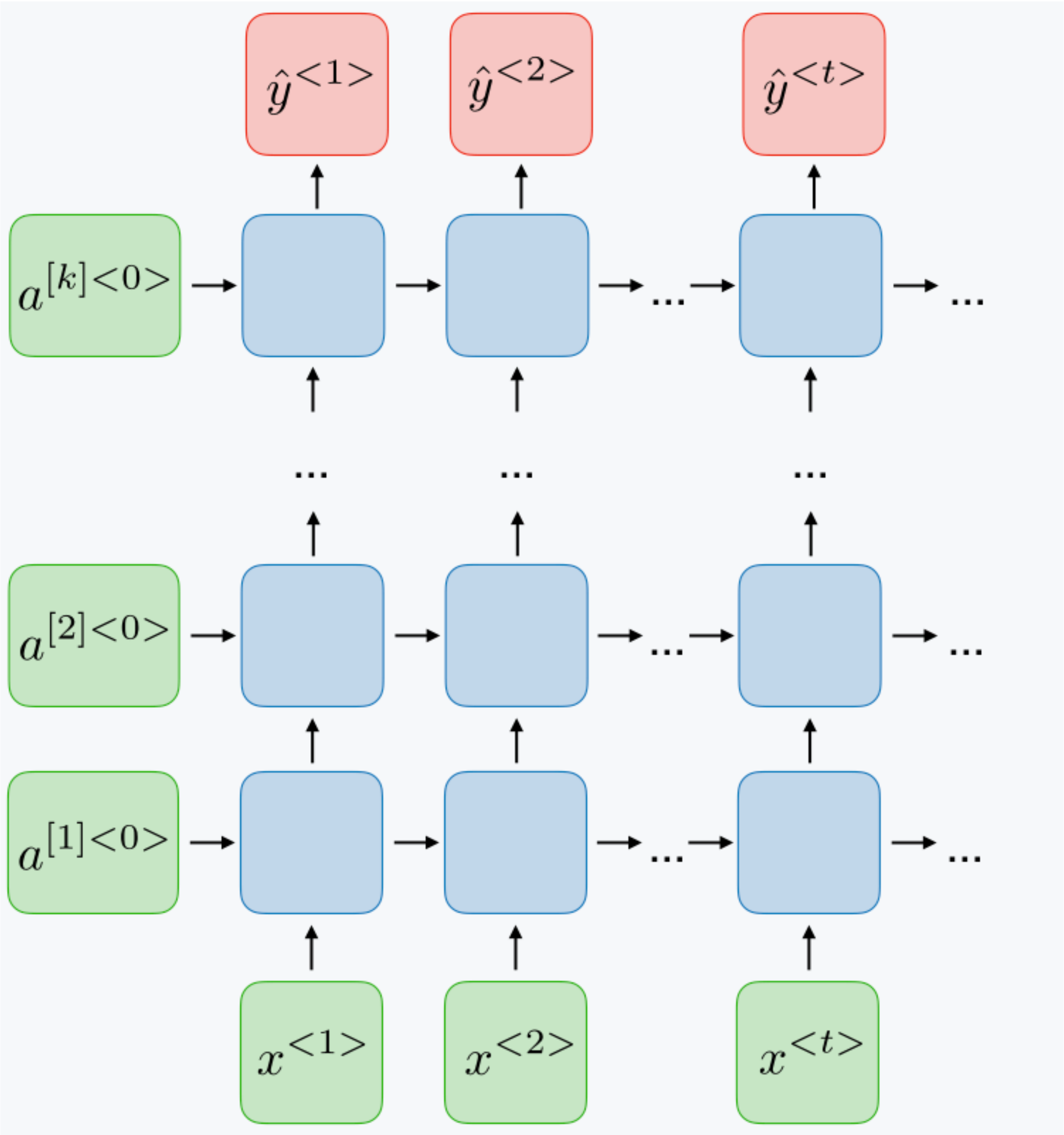

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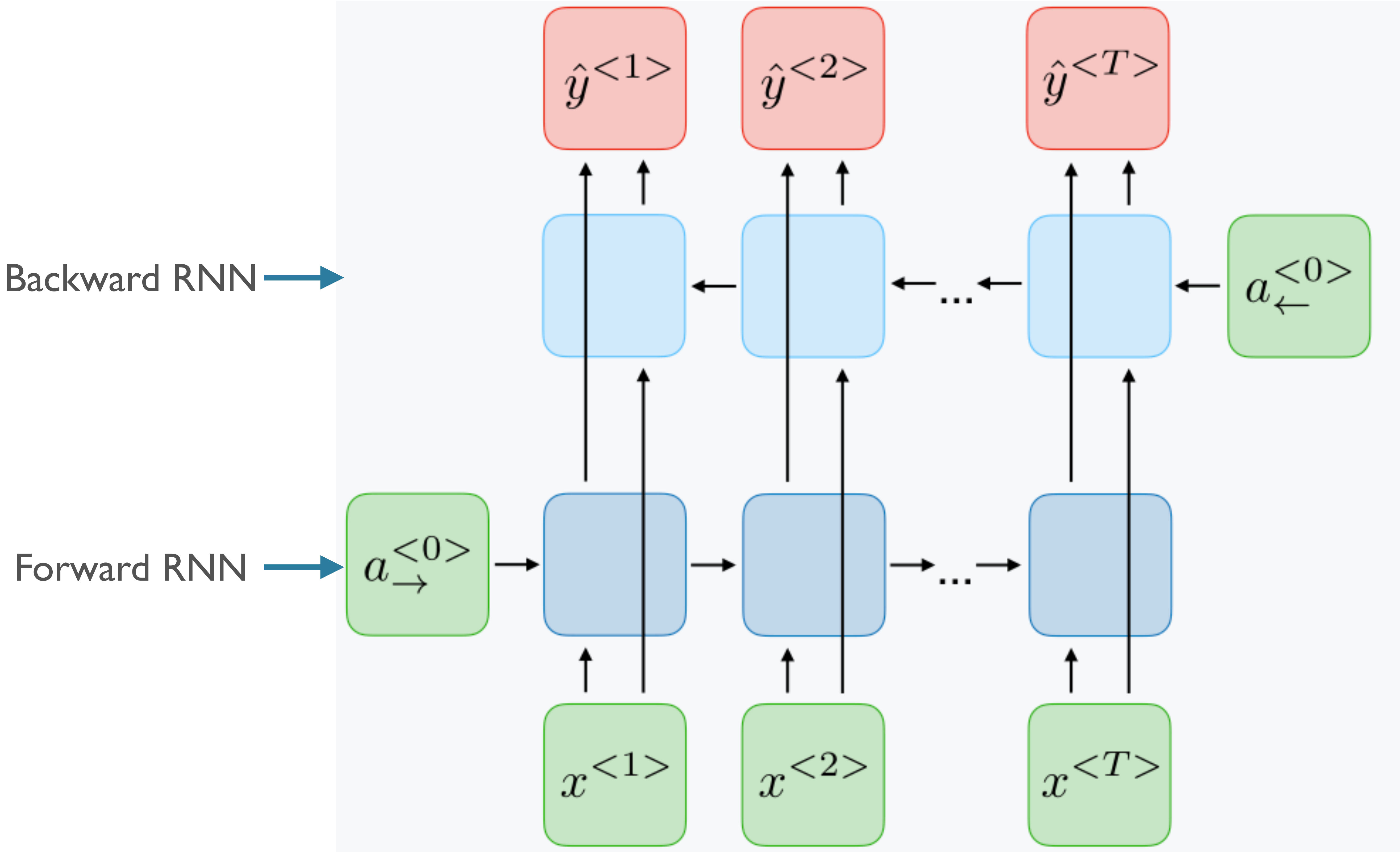

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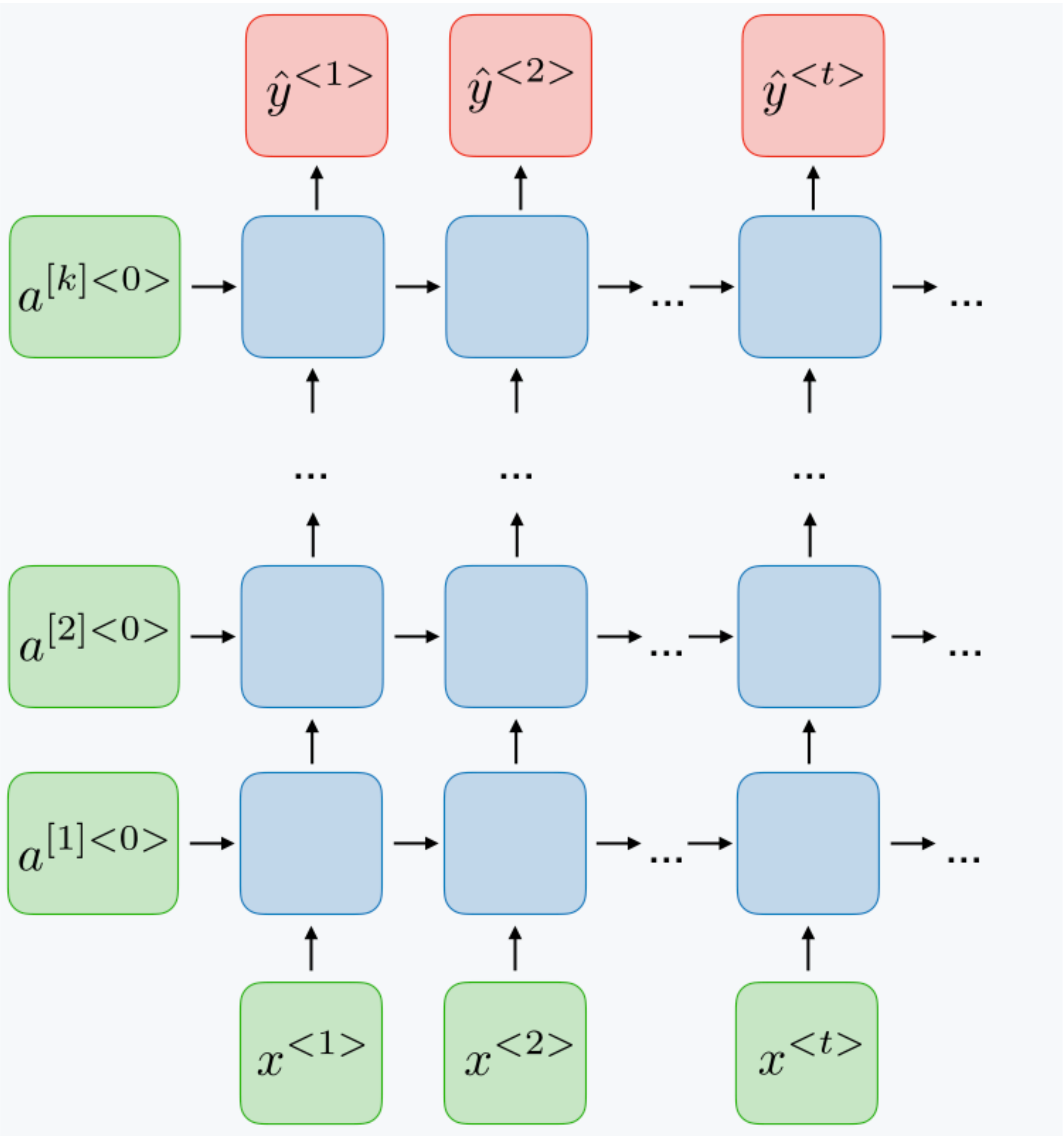

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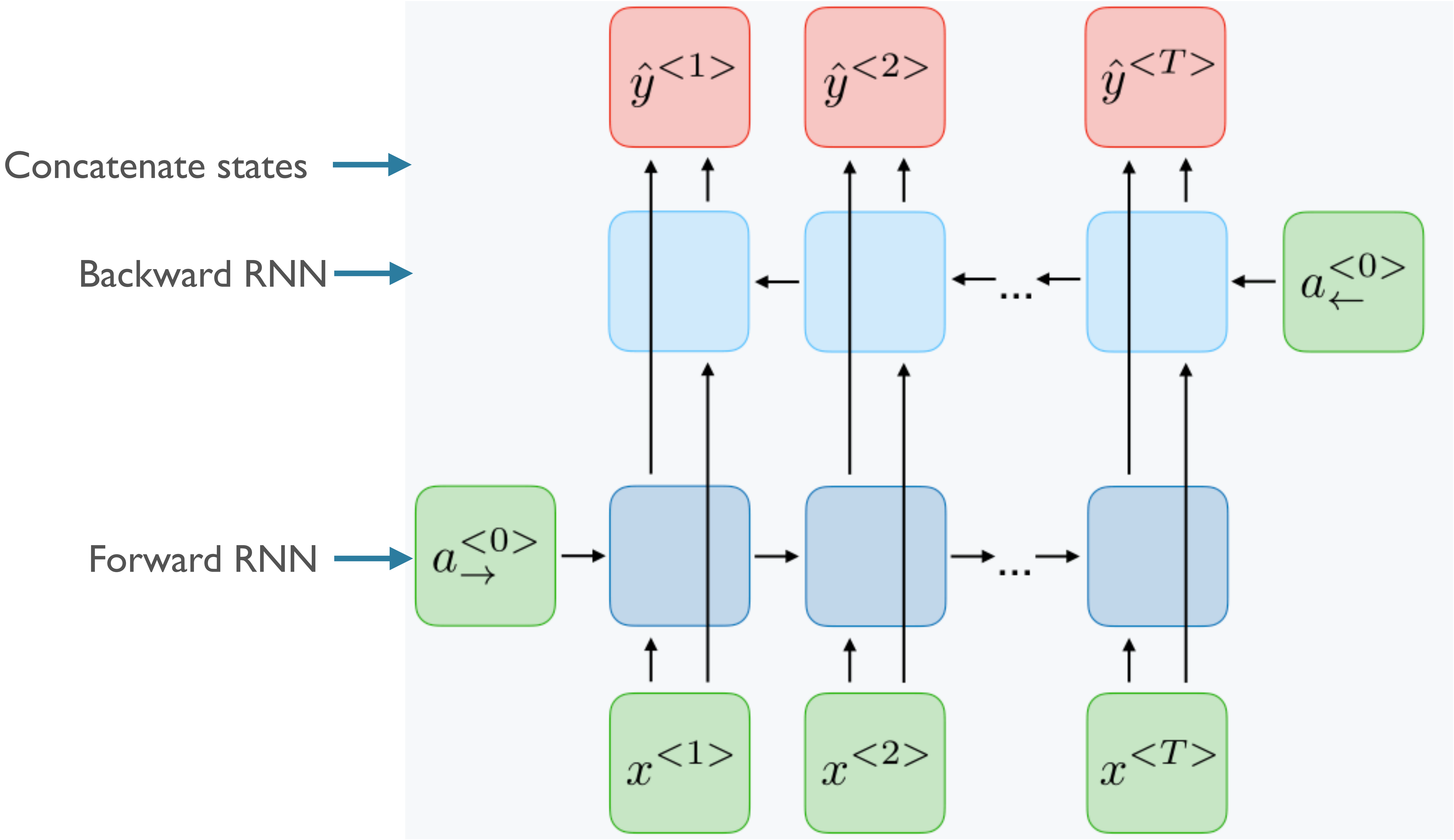

Source: RNN cheat sheet

Batching in RNNs

- Intuitively, shape of inputs: [batch_size, seq_len, vocab_size]
- But what is sequence length??
  - “This is the first example </s>”: 6
  - “This is another </s>”: 4

Padding and Masking

- Step 1: *pad* all sequences in batch to be of the same length
  - “This is the first example </s>”: 6
  - “This is another </s> PAD PAD”: 6
- Step 2: build a “mask” (1 = True token, 0 = padding)

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 \end{bmatrix}$$

- Step 3: use mask to tell model what to ignore, either
  - Select correct final states [classification]
  - Multiply losses in tagging tasks [LM]

Summary

- RNNs allow for neural processing of *sequential data*
- In principle, should help models capture long-distance dependencies (e.g. number agreement, selectional preferences, …)
  - Maintain a state over time
  - Repeatedly apply the same weights
  - as opposed to n-gram models, which cannot build such dependencies
- Uses: classification, tagging
- Extensions: deep, bidirectional

Next Time

- Discuss a technical problem in training Vanilla RNNs
  - Vanishing gradients
- Introduce *gating-based* RNNs
  - LSTMs
  - GRUs
  - Strengths, weaknesses, differences