Recurrent Neural Networks 1

Ling 282/482: Deep Learning for Computational Linguistics

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Fall 2024

Today's Plan

- Last time:
  - Feed-forward models for NLP tasks
  - Deep Averaging Network (DAN)
  - Neural Probabilistic Language Model
  - Additional Training Notes
    - Regularization
    - Early stopping
    - Hyper-parameter searching
- Today: intro to *Recurrent* Neural Networks

Announcements

- 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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- Feed-forward networks: **fixed-size** input, fixed-size output
  - DAN classifier: average embeddings of words
  - Feedforward LM: n-gram assumption (i.e. **fixed-size context** of word embeddings)

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- RNNs process **sequences** of vectors
  - Maintaining “hidden” state
  - Applying the **same operation at each step**

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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: agreement

- 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

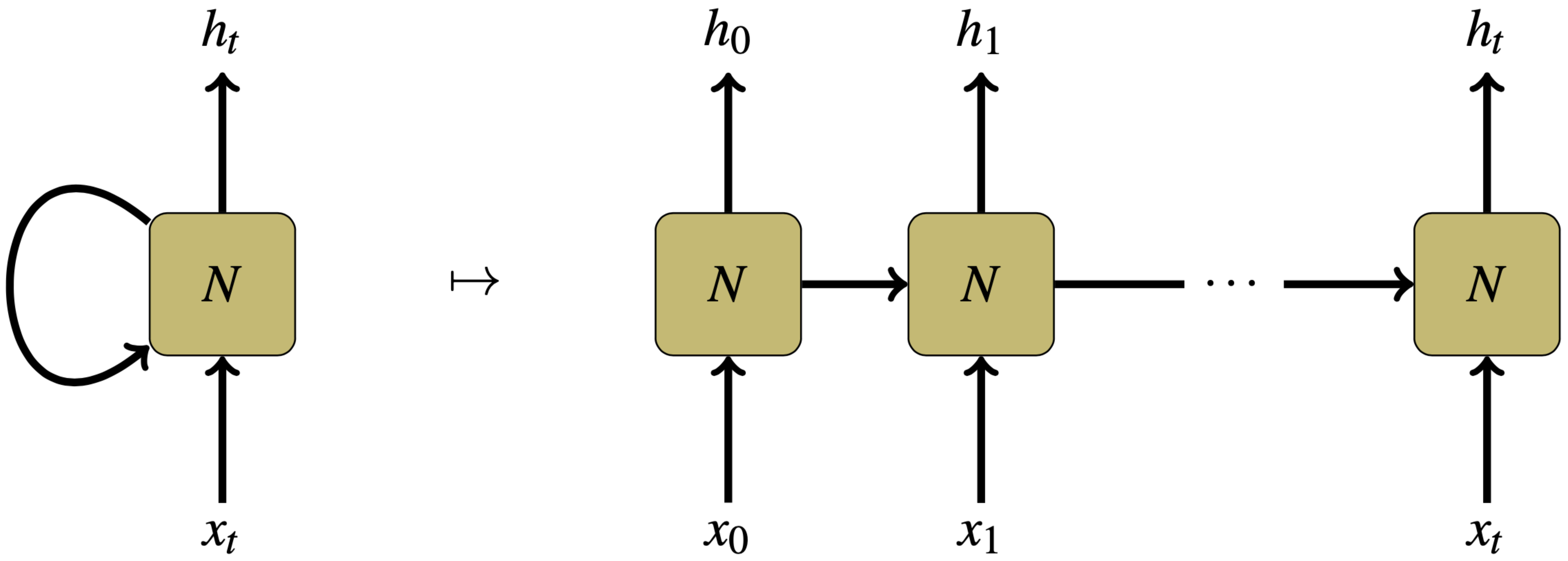
Selectional Restrictions

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

Selectional Restrictions

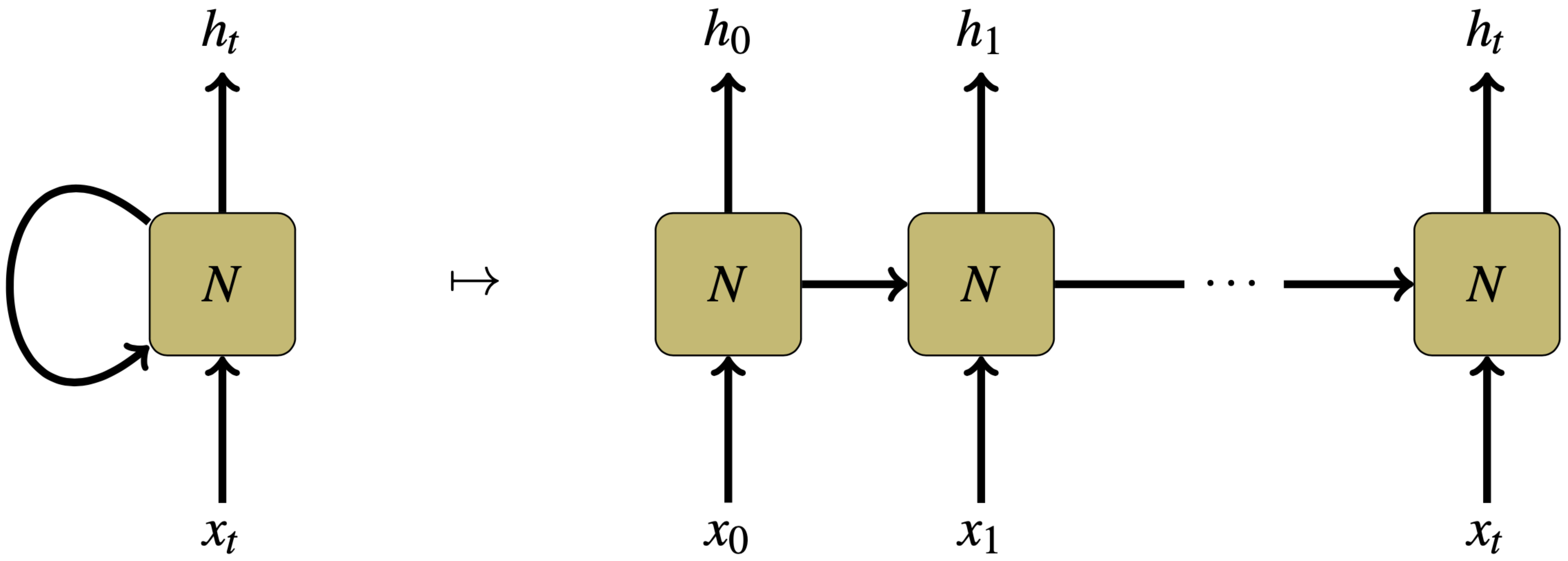
- The **family** moved from the city because they wanted a larger **house**.
- The **team** moved from the city because they wanted a larger **market**.
- Need models that can capture long-range dependencies like this.
- N-gram (whether count-based or neural) **cannot** (e.g. with n=4)
  - P(word | “they wanted a larger”)

RNNs



Steinert-Threlkeld and Szymanik 2019; Olah 2015

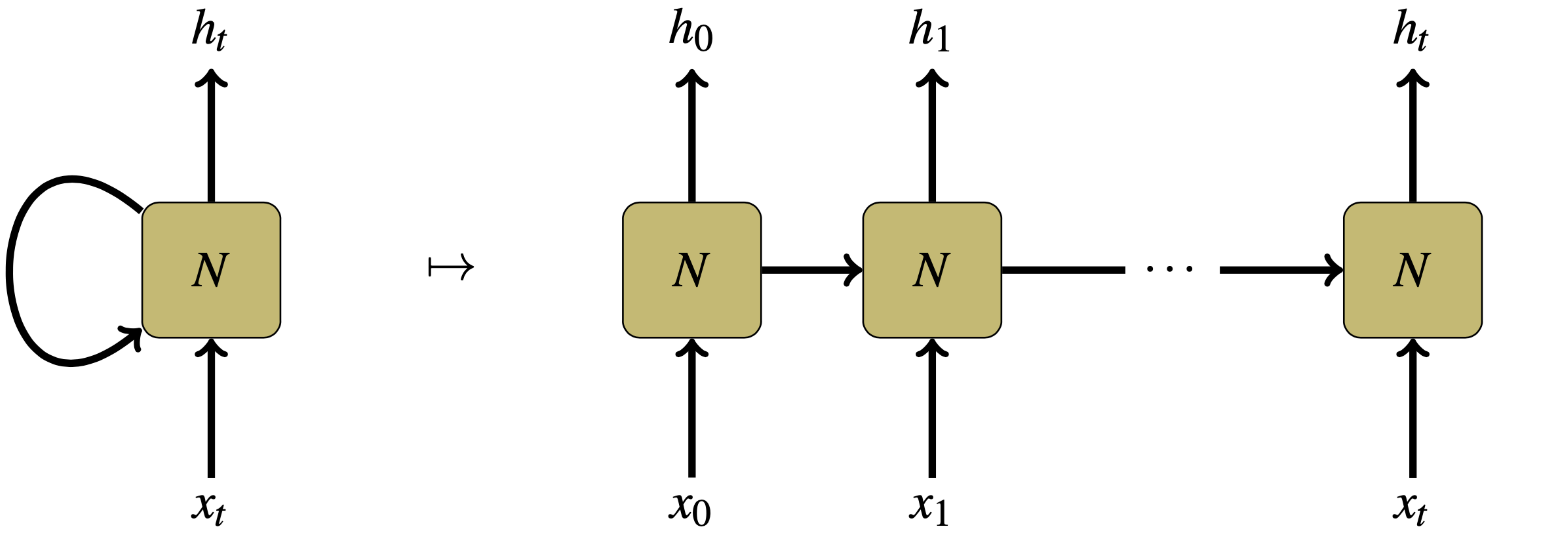
RNNs



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

Steinert-Threlkeld and Szymanik 2019; Olah 2015

RNNs



This class … interesting

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

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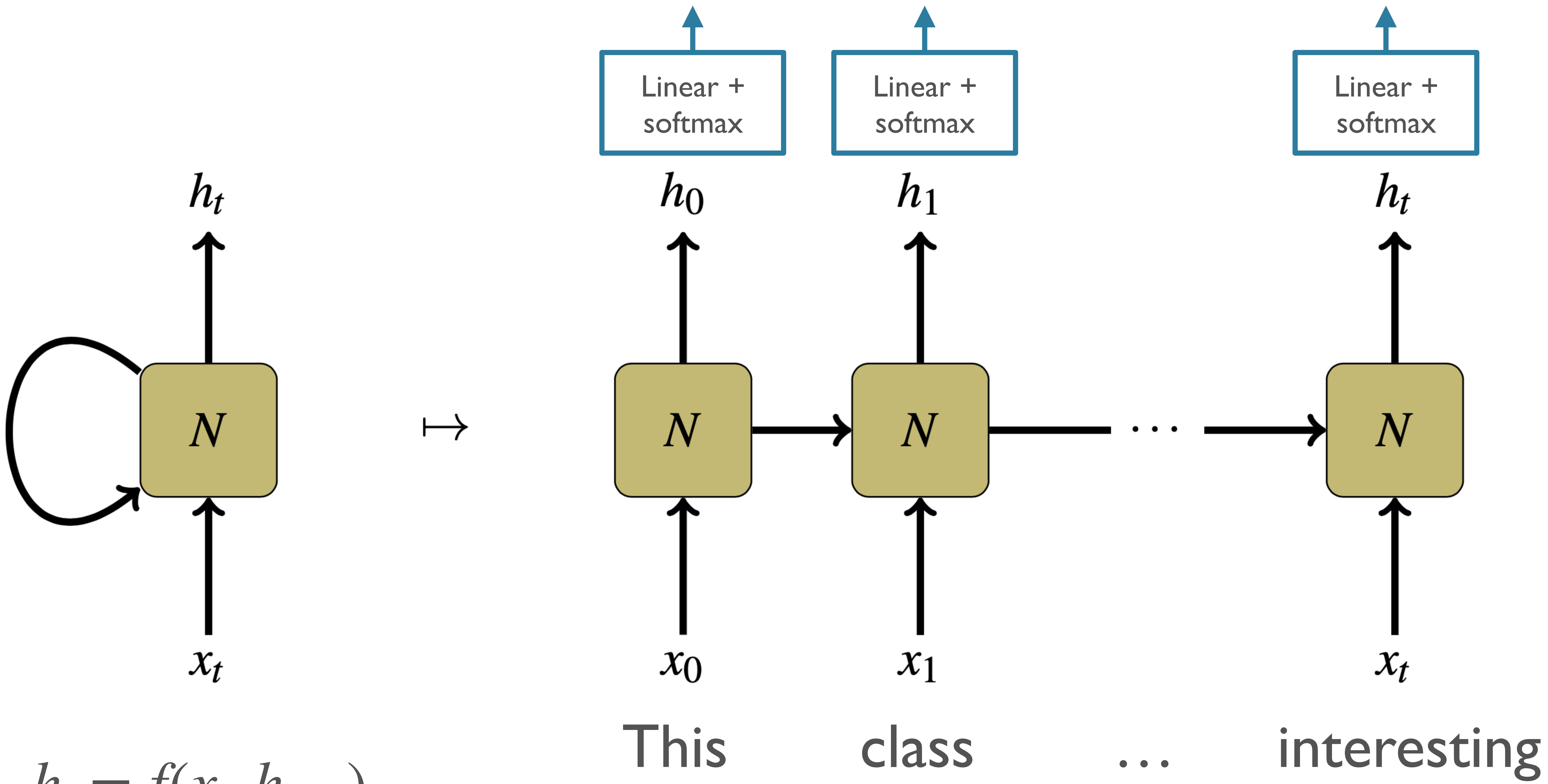
RNNs



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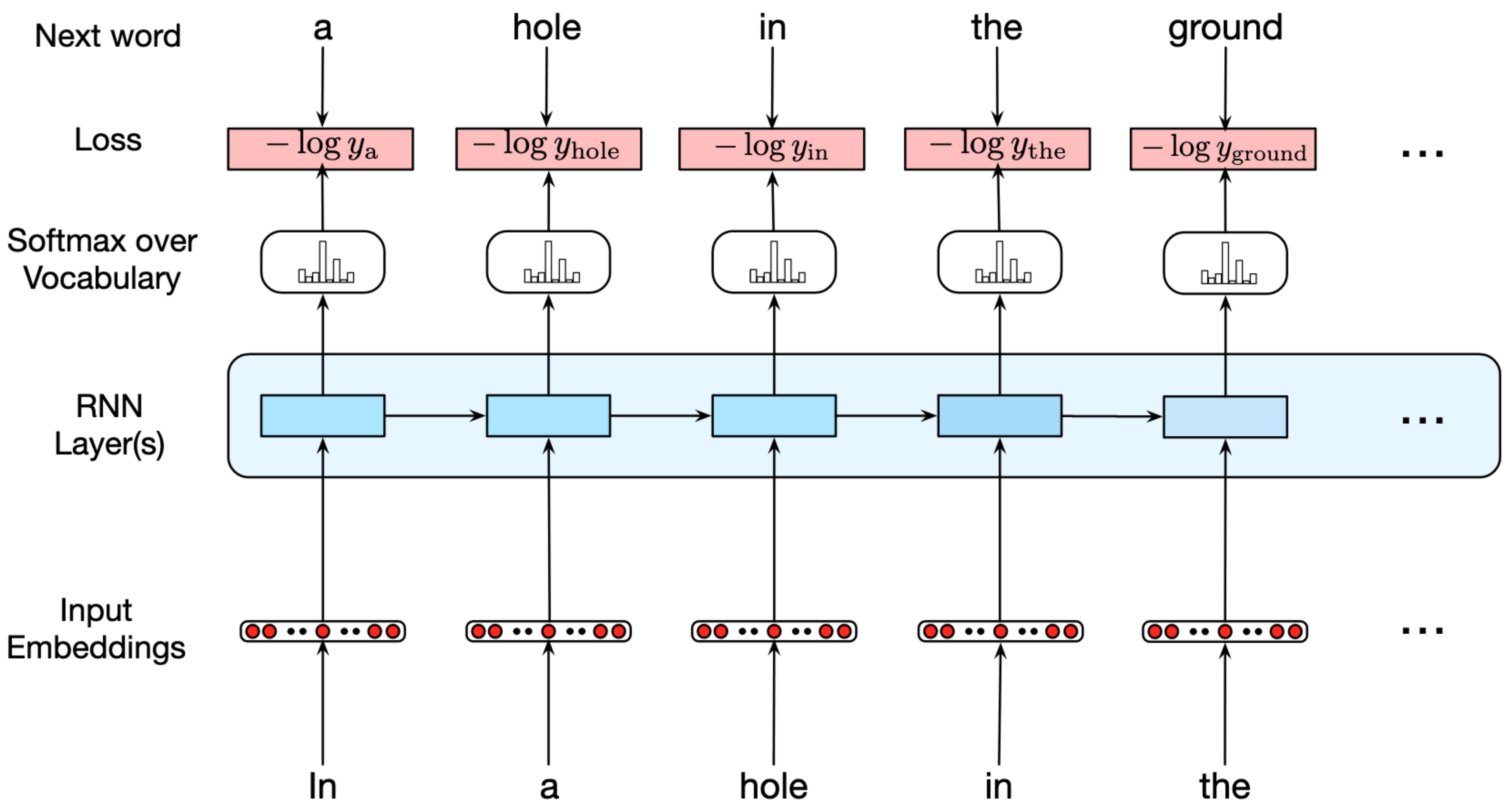
Simple/"Vanilla" RNN: $$h_t = \tanh(W_x x_t + W_h h_{t-1} + b)$$

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

"Unrolled" RNN

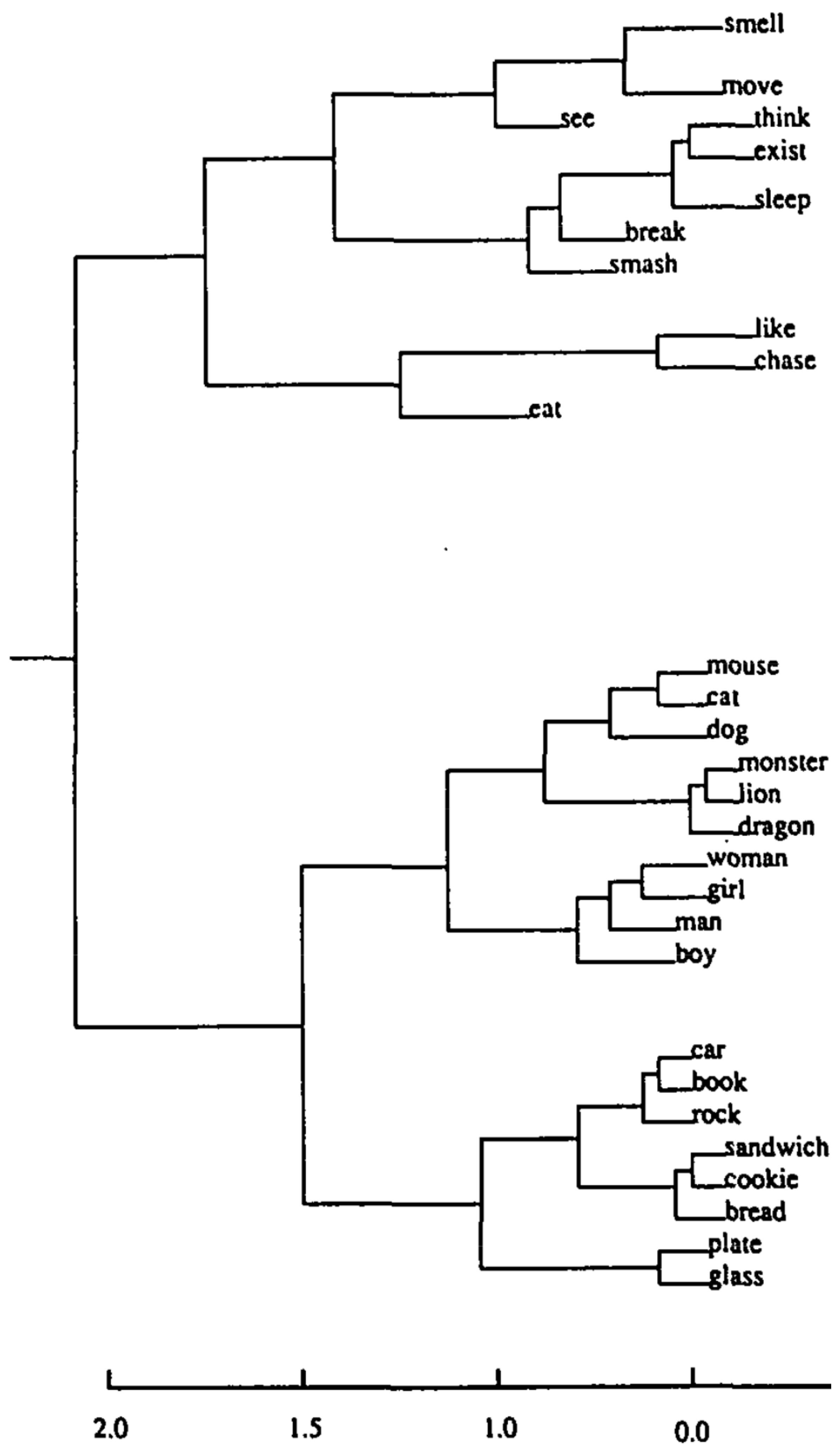


$$\frac{1}{T}\sum_{t=1}^{T} L_{CE}$$

JM sec 9.2.3

Power of RNNs

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



What trends do you notice?

Elman 1990

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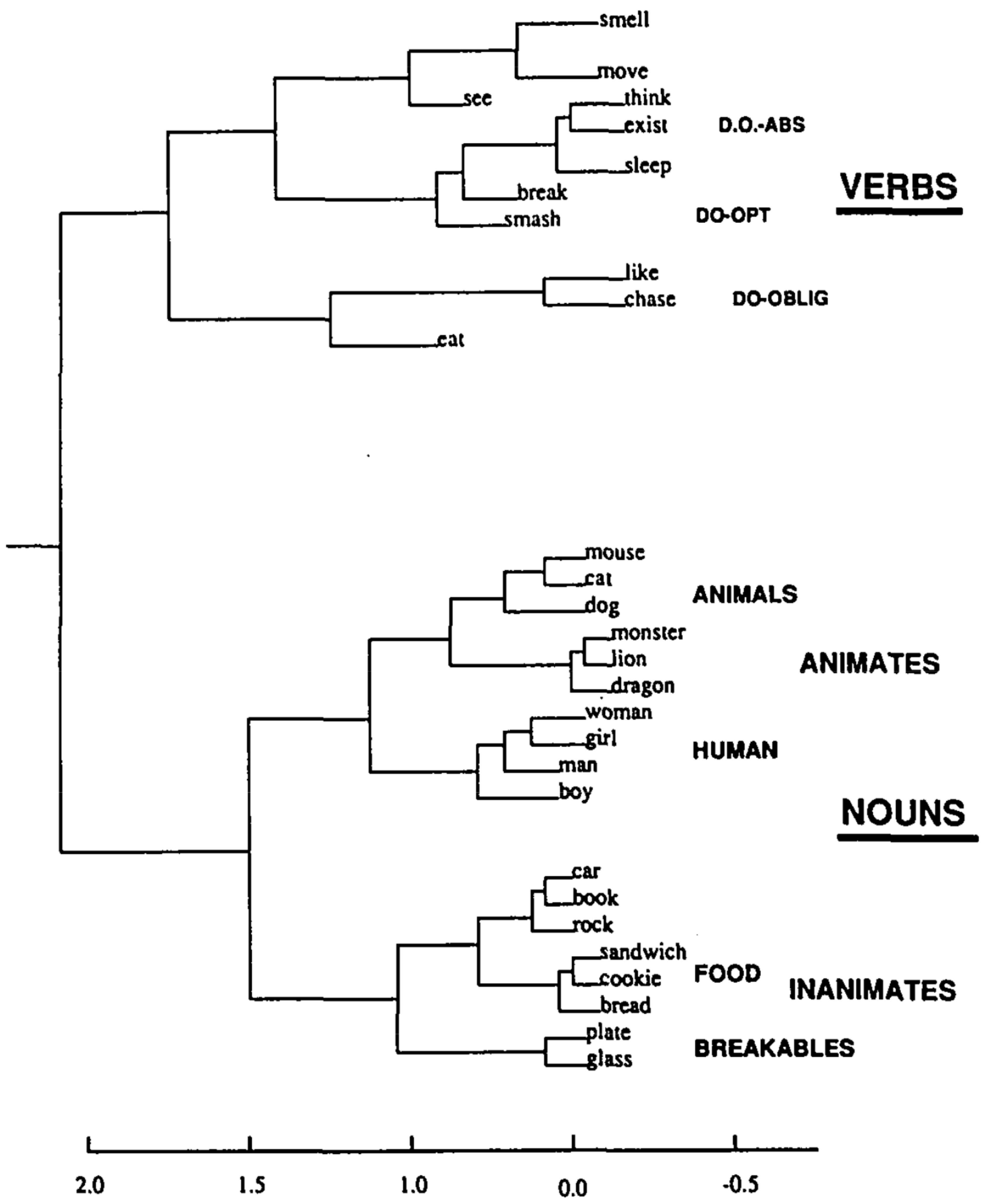
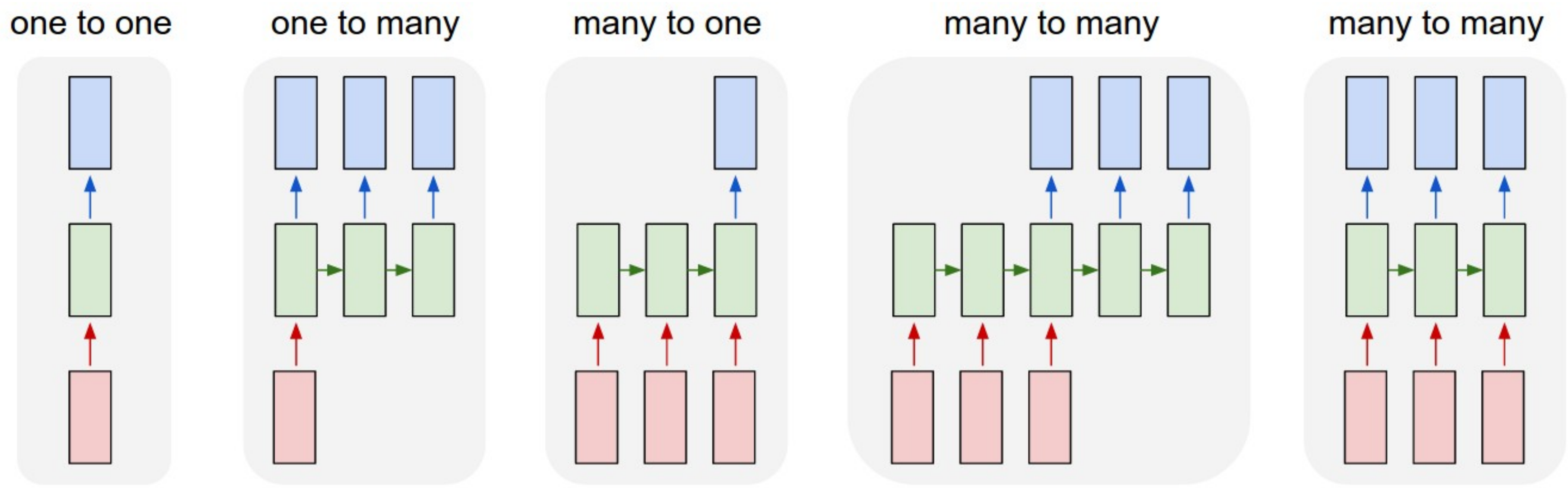


Elman 1990

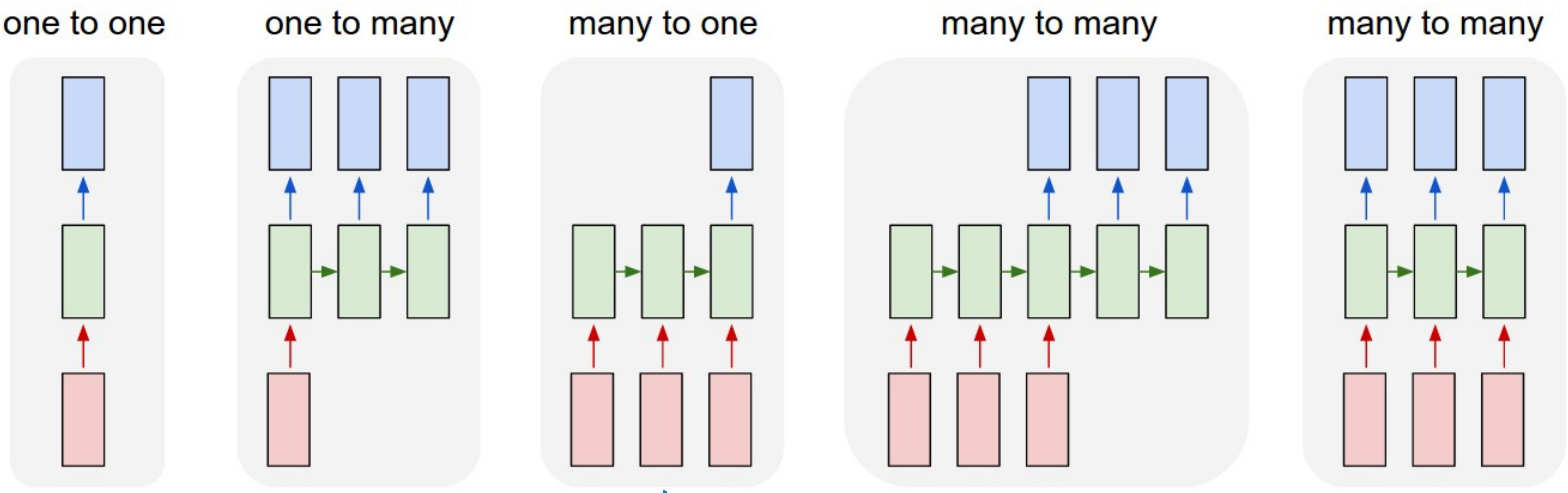
Using RNNs



MLP

e.g. image captioning

Using RNNs



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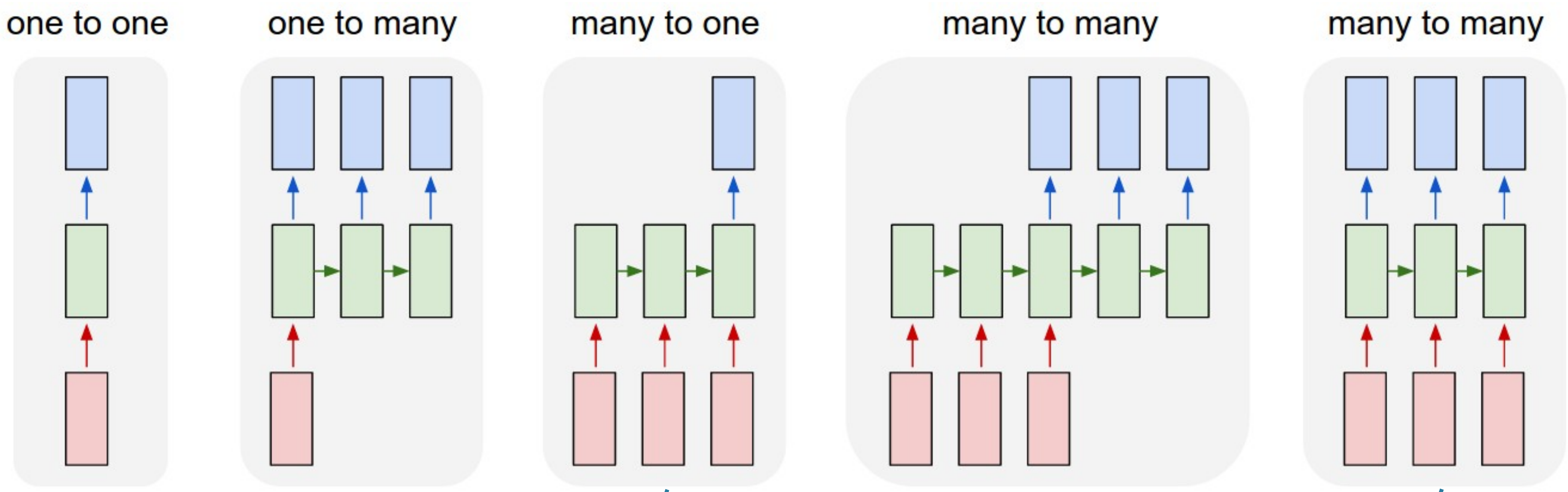
e.g. image captioning

e.g. text classification

Using RNNs



MLP

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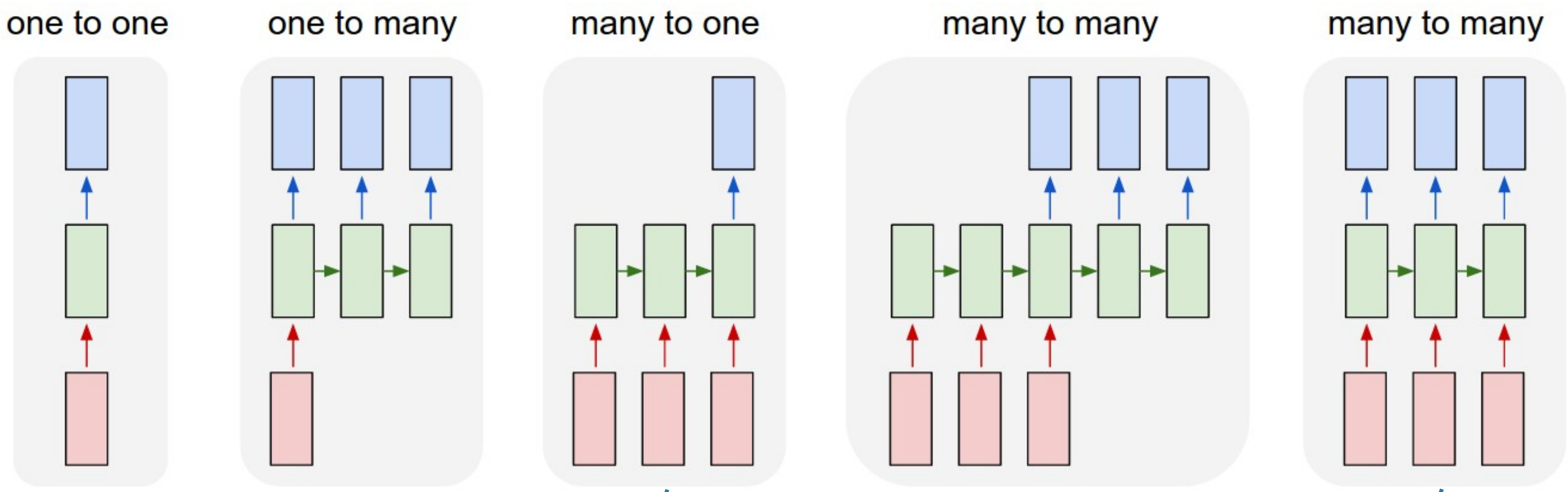
e.g. text classification

e.g. POS tagging

Using RNNs



MLP

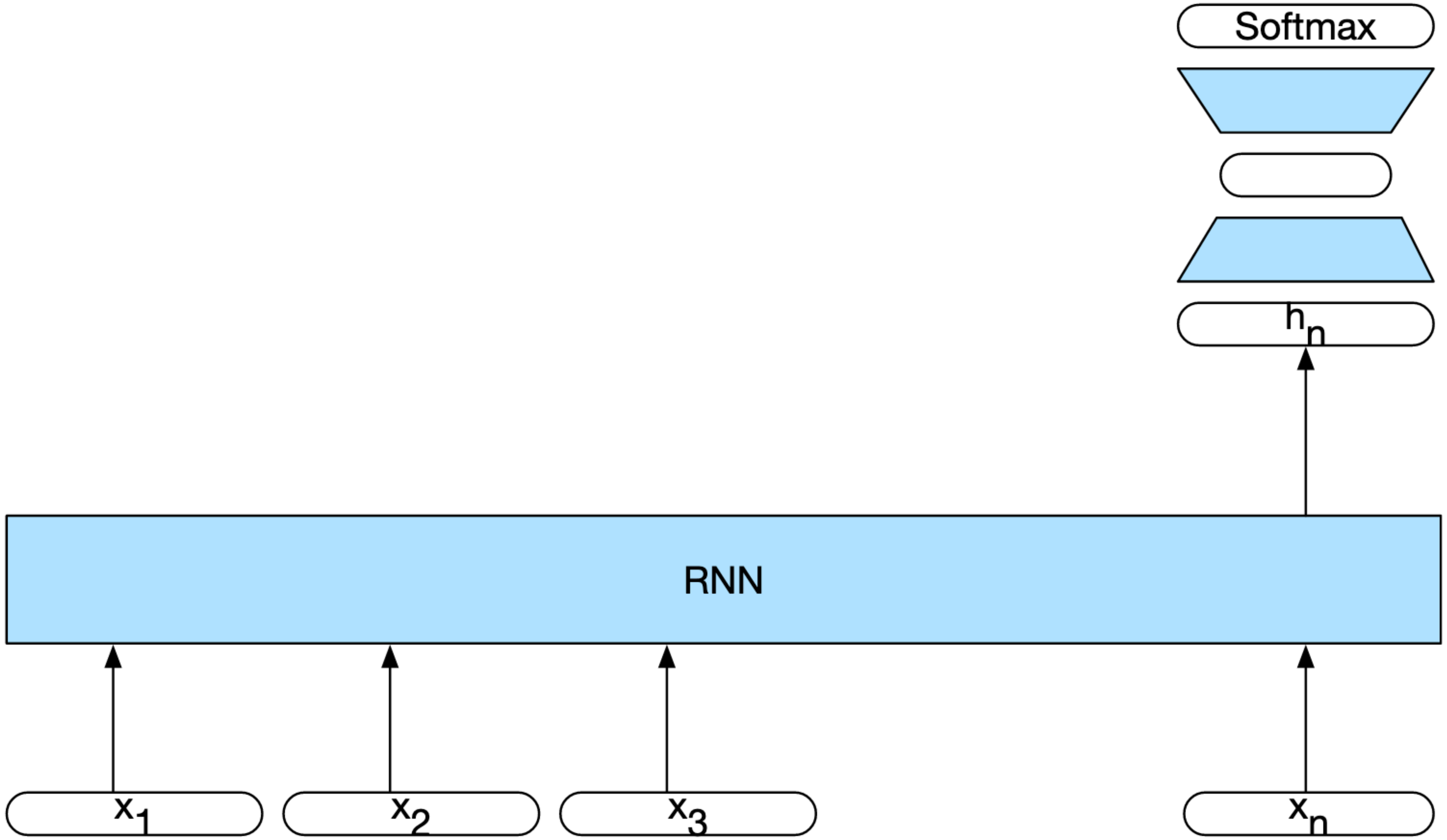
e.g. image captioning

seq2seq (later)

e.g. text classification

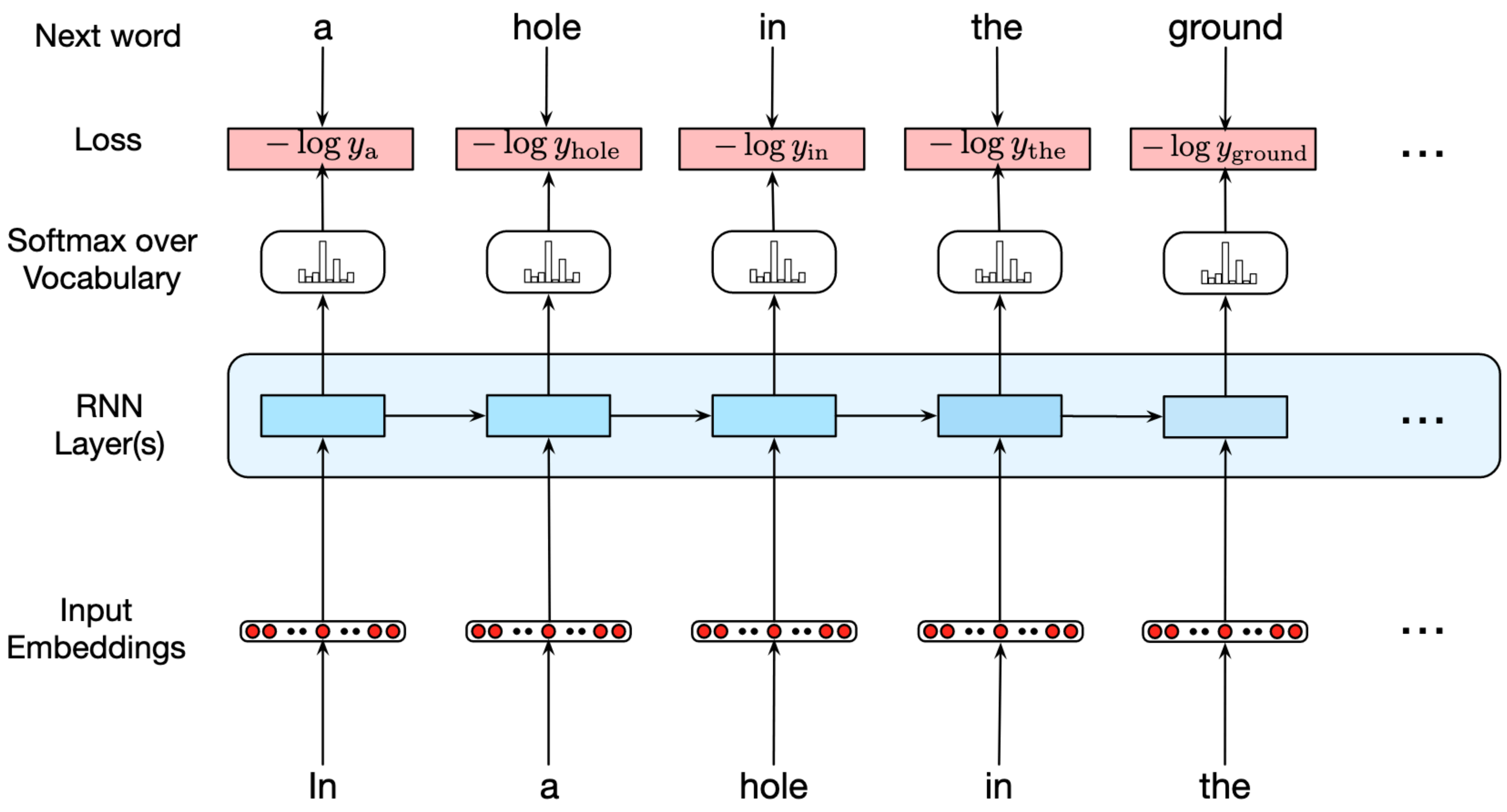
e.g. POS tagging

RNN for Text Classification



JM sec 9.2.5

RNNs for Language Modeling

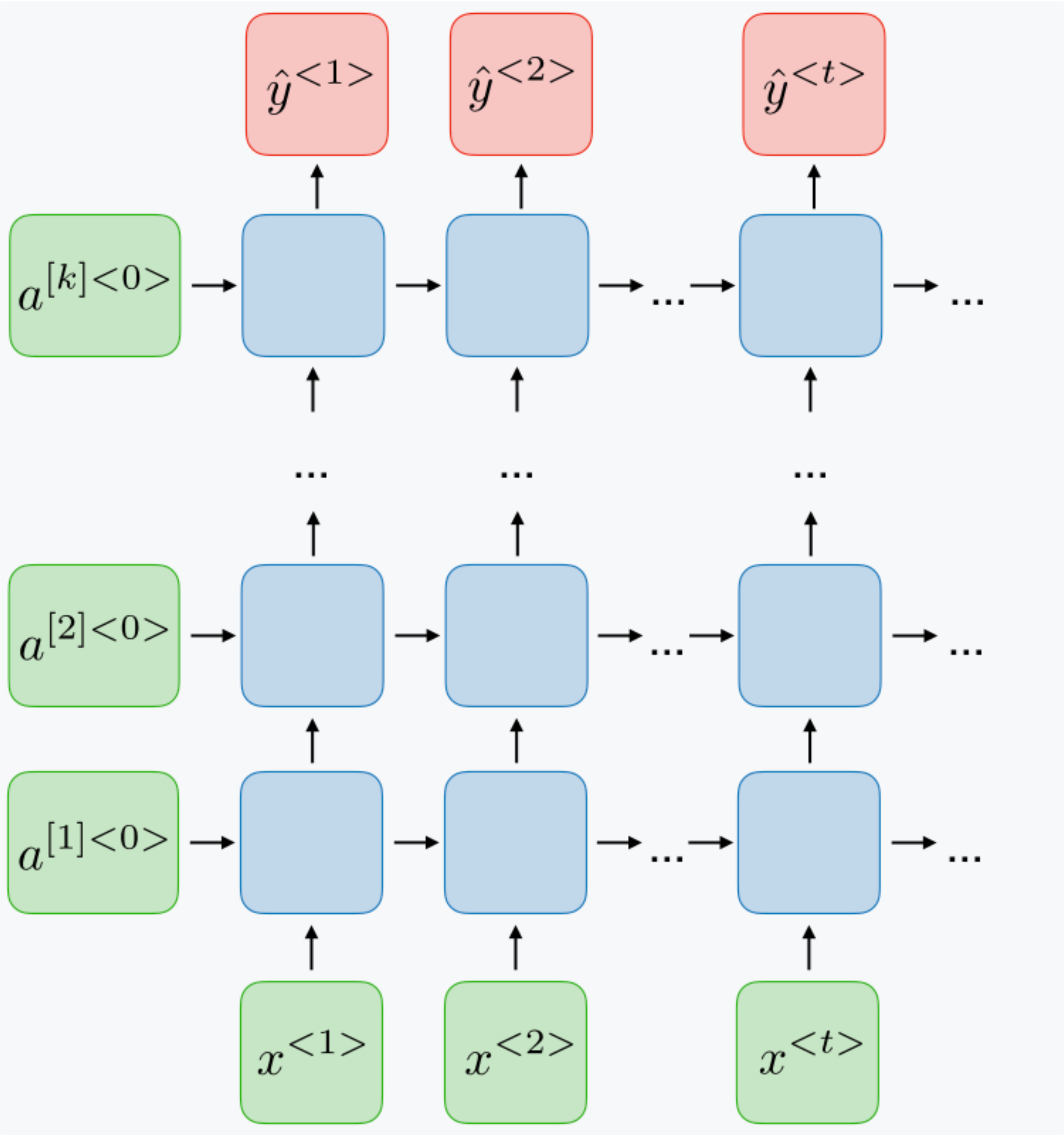


$$\frac{1}{T}\sum_{t=1}^{T} L_{CE}$$

JM sec 9.2.3

Two Extensions

- Deep RNNs:



Source: RNN cheat sheet

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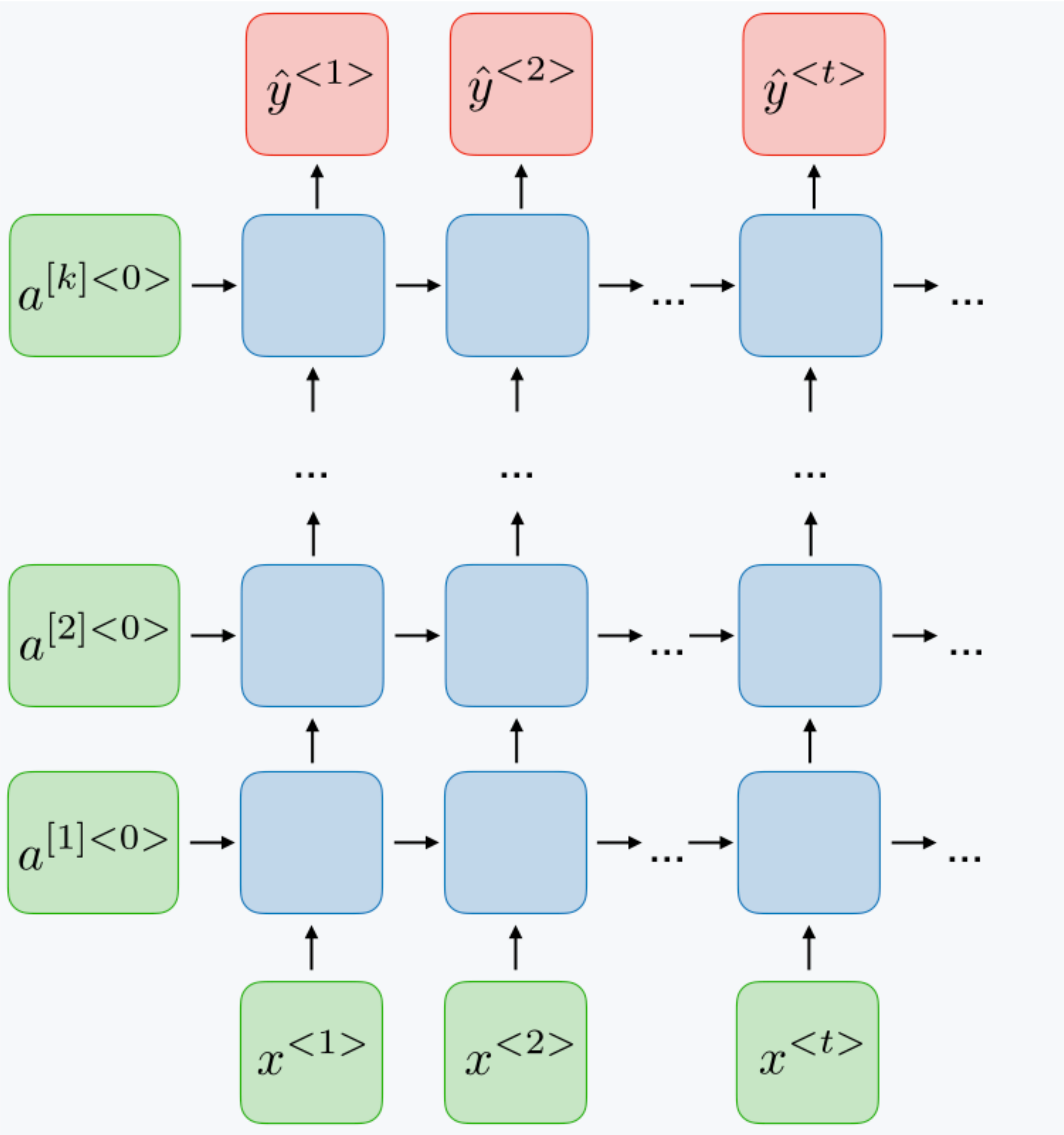
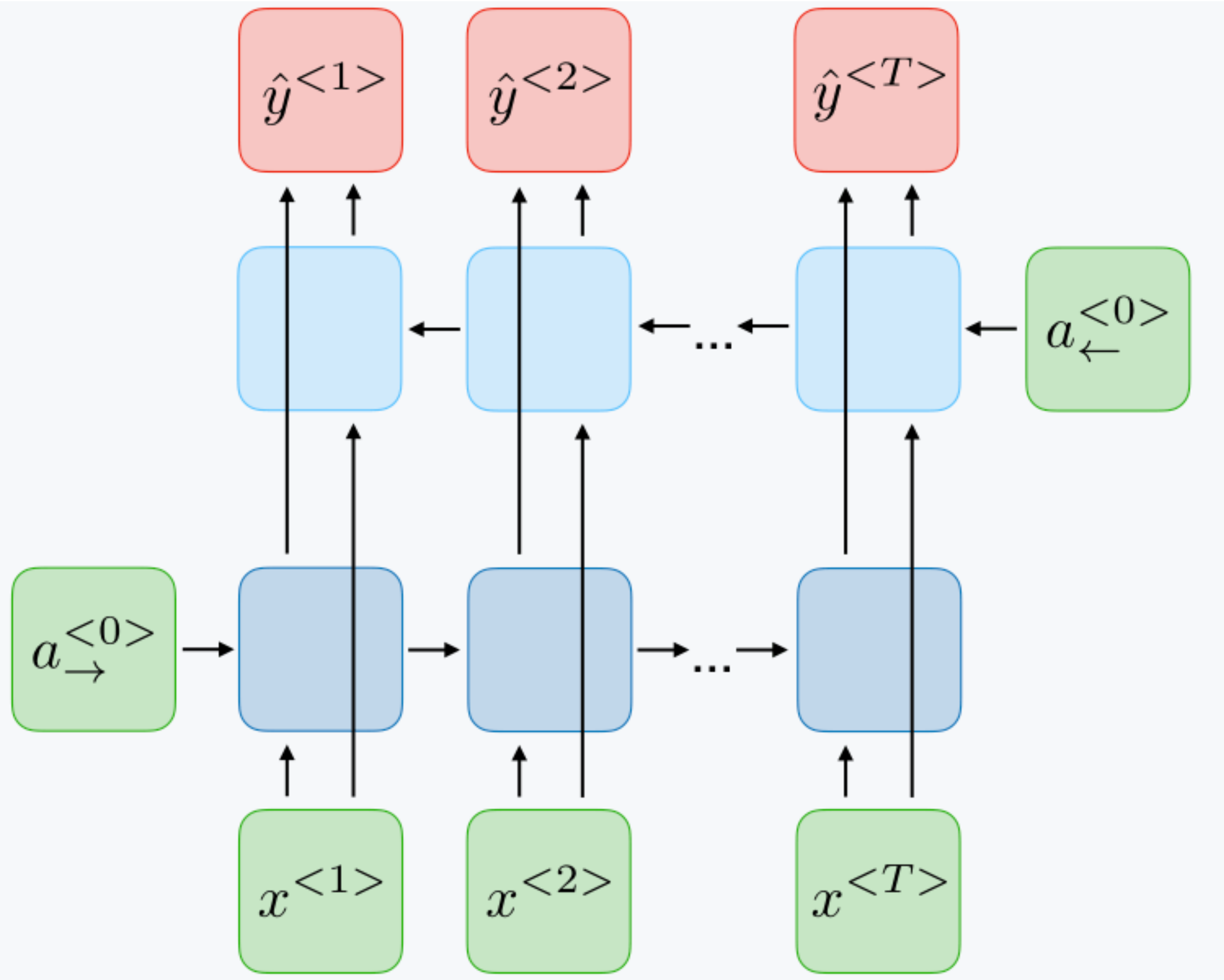


- Bidirectional RNNs:



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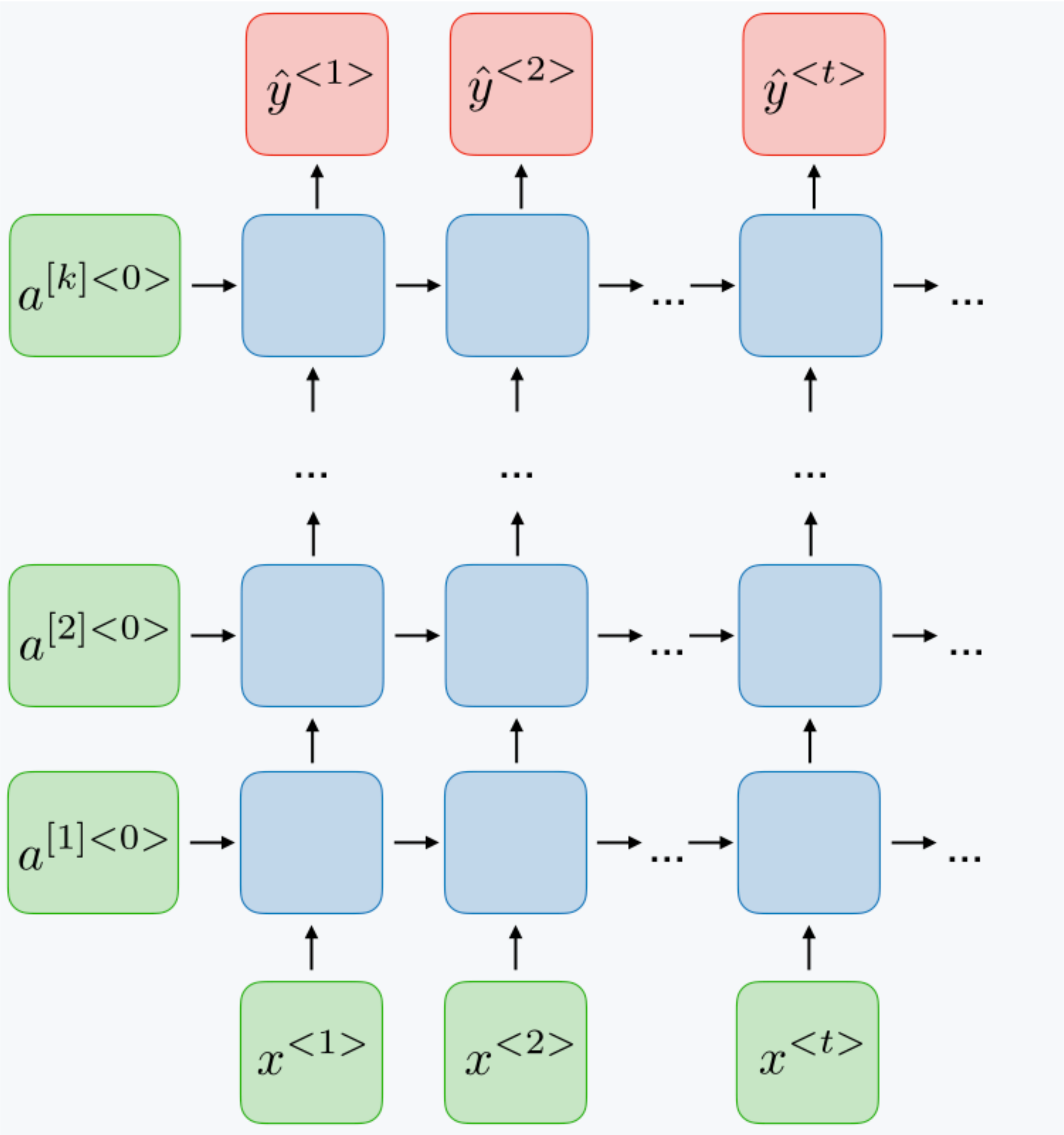

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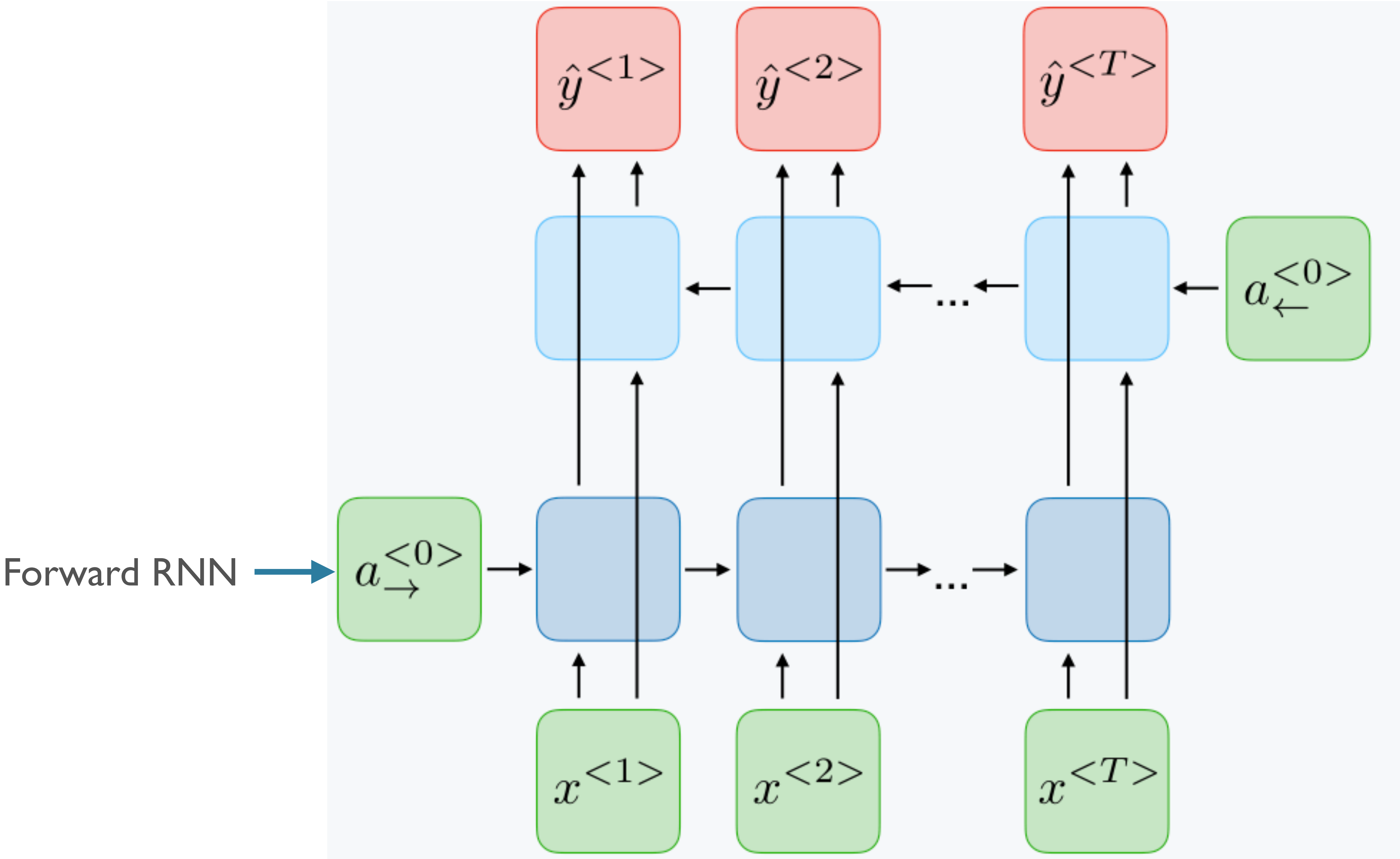

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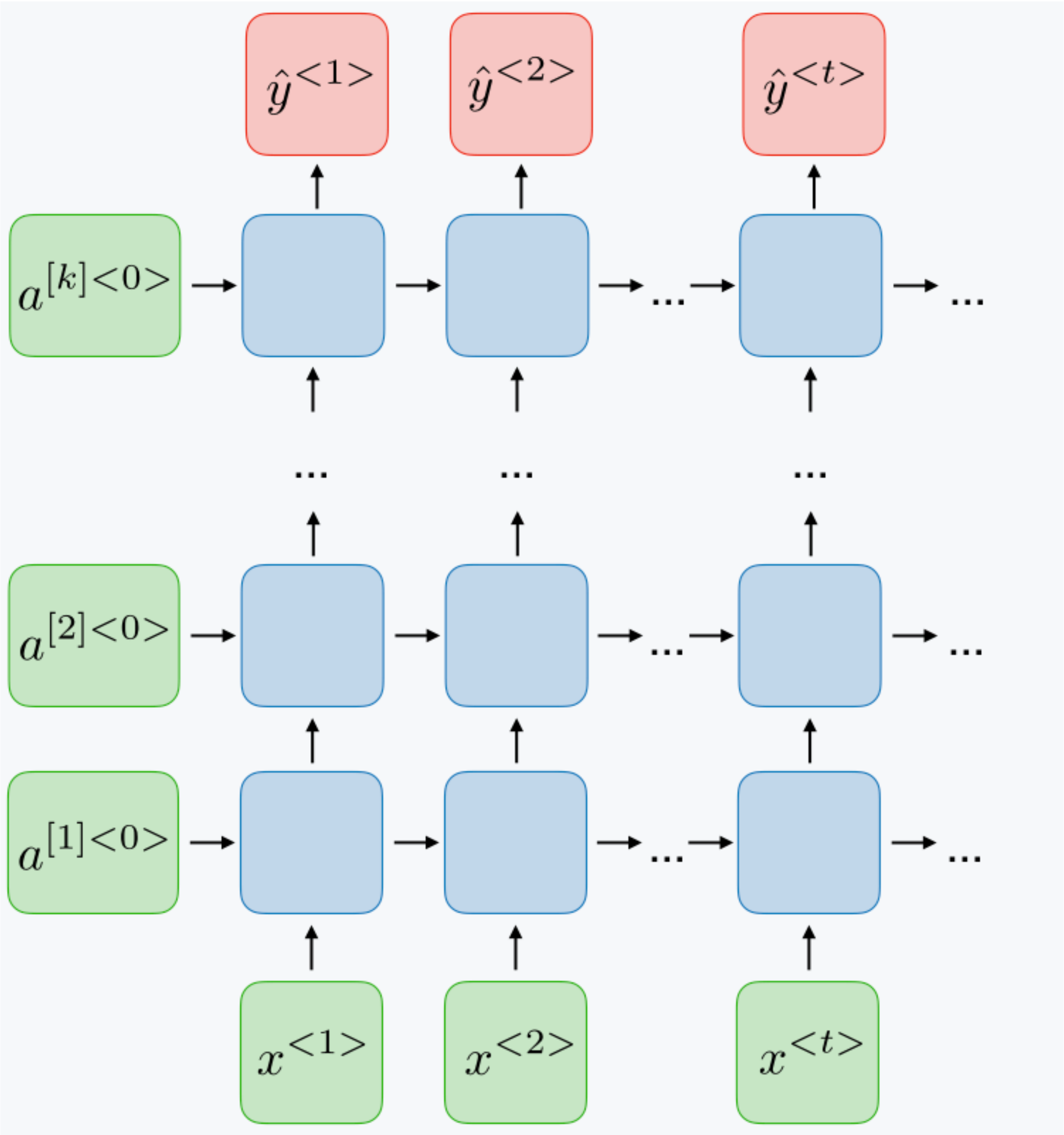

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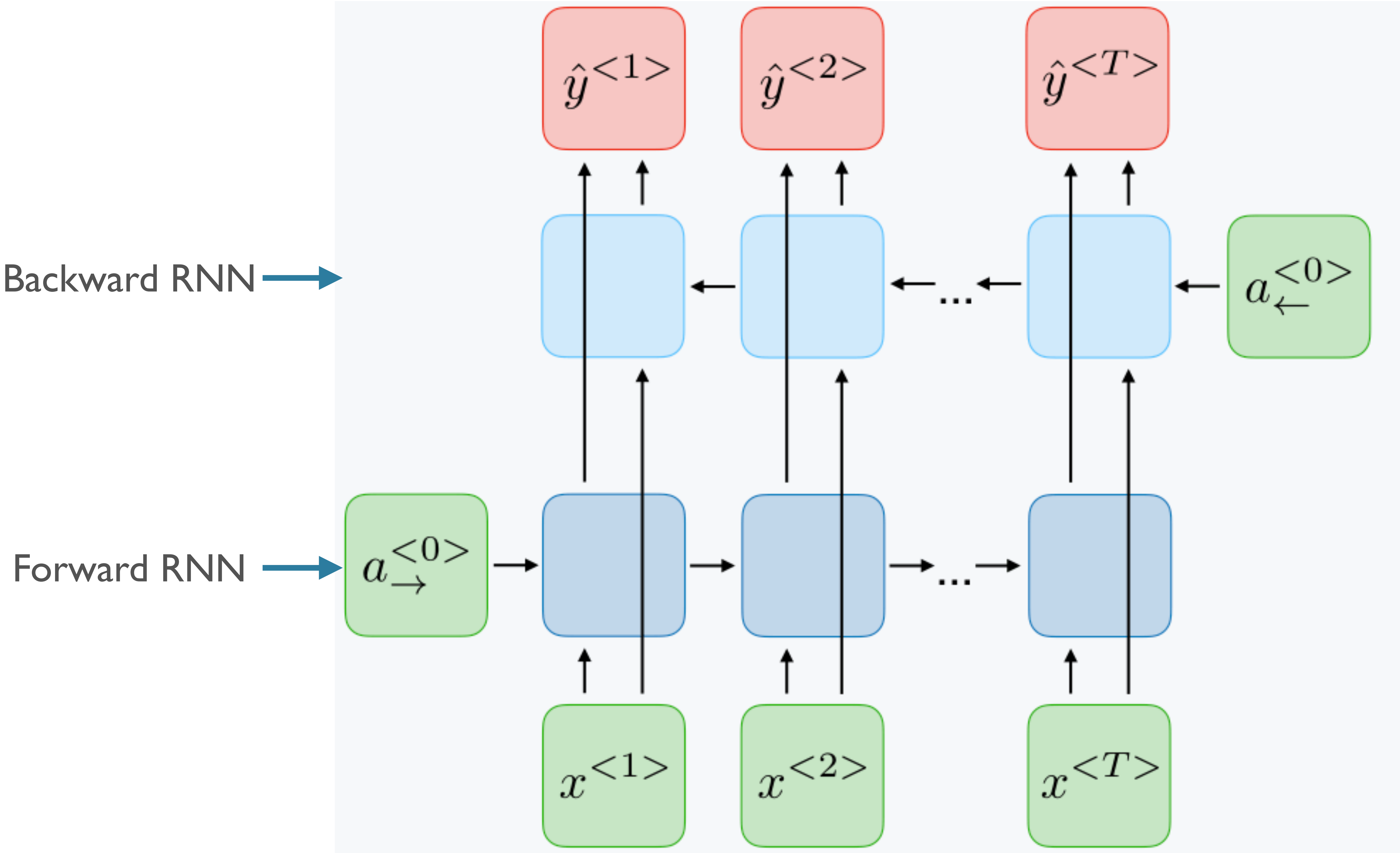

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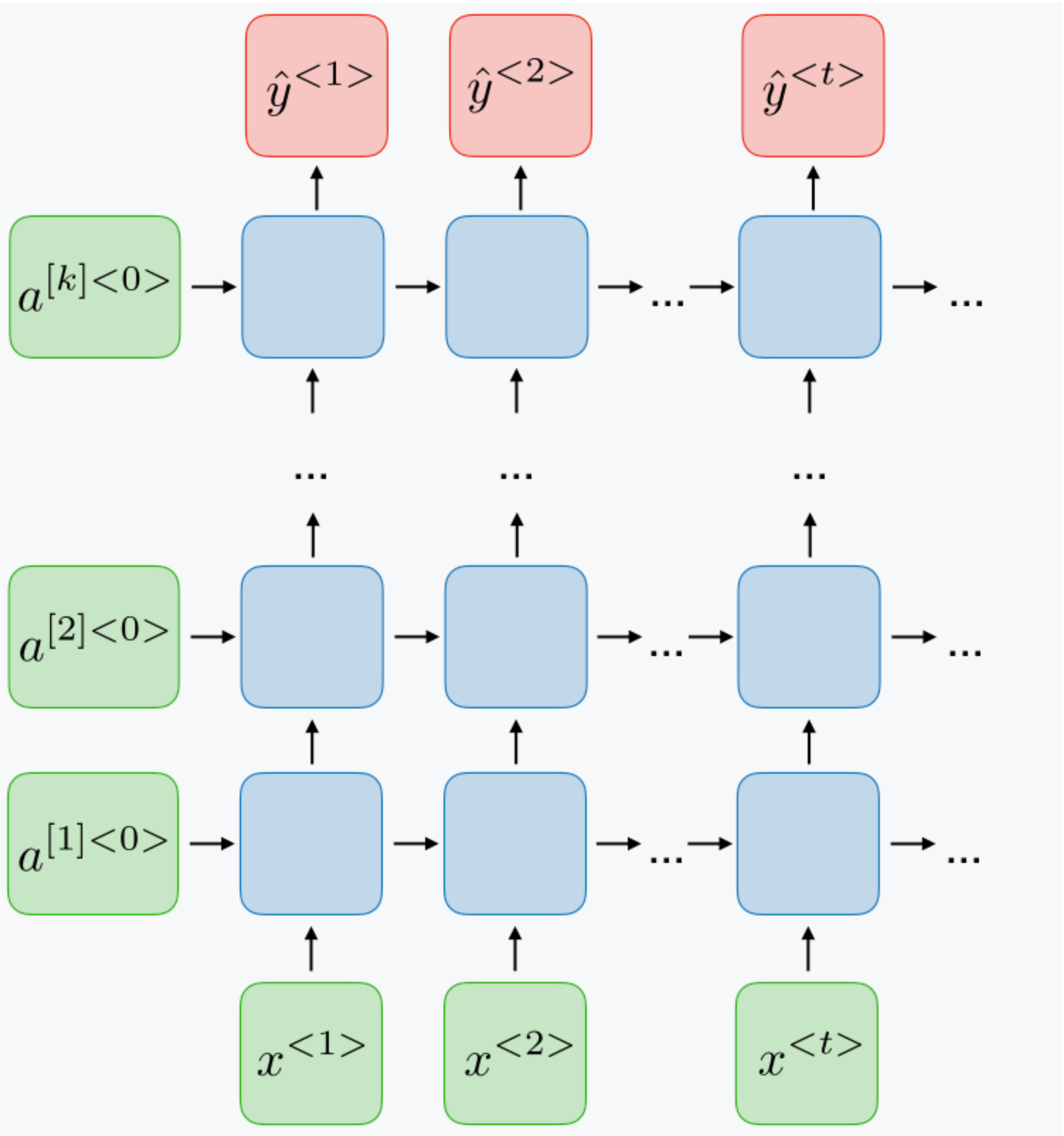

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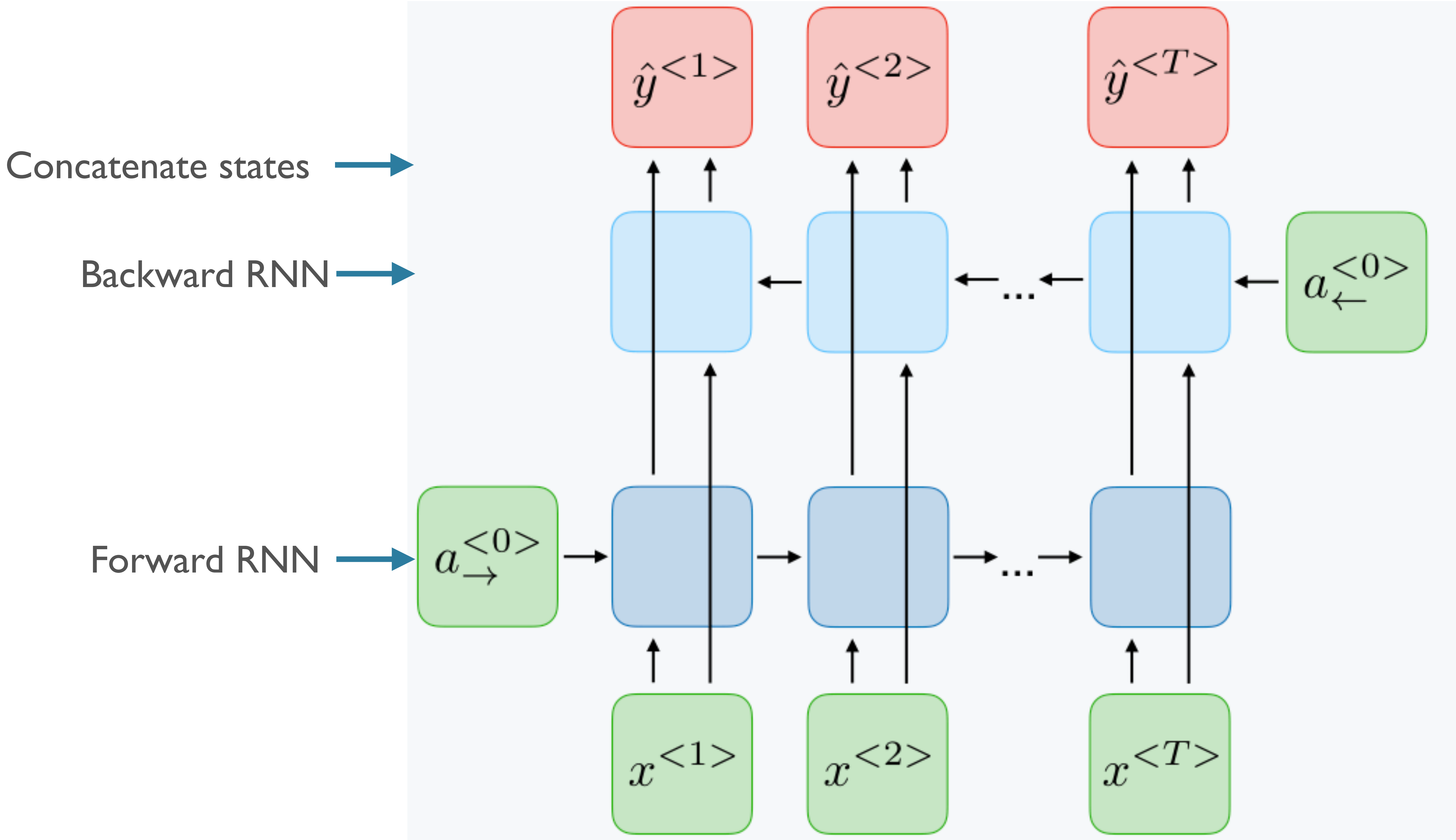

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Batching in RNNs

- 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