Recurrent Neural Networks

Ling 282/482: Deep Learning for Computational Linguistics

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Fall 2025

RNNs: high-level

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- Feed-forward networks: **fixed-size** input, fixed-size output
  - Feedforward 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: 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

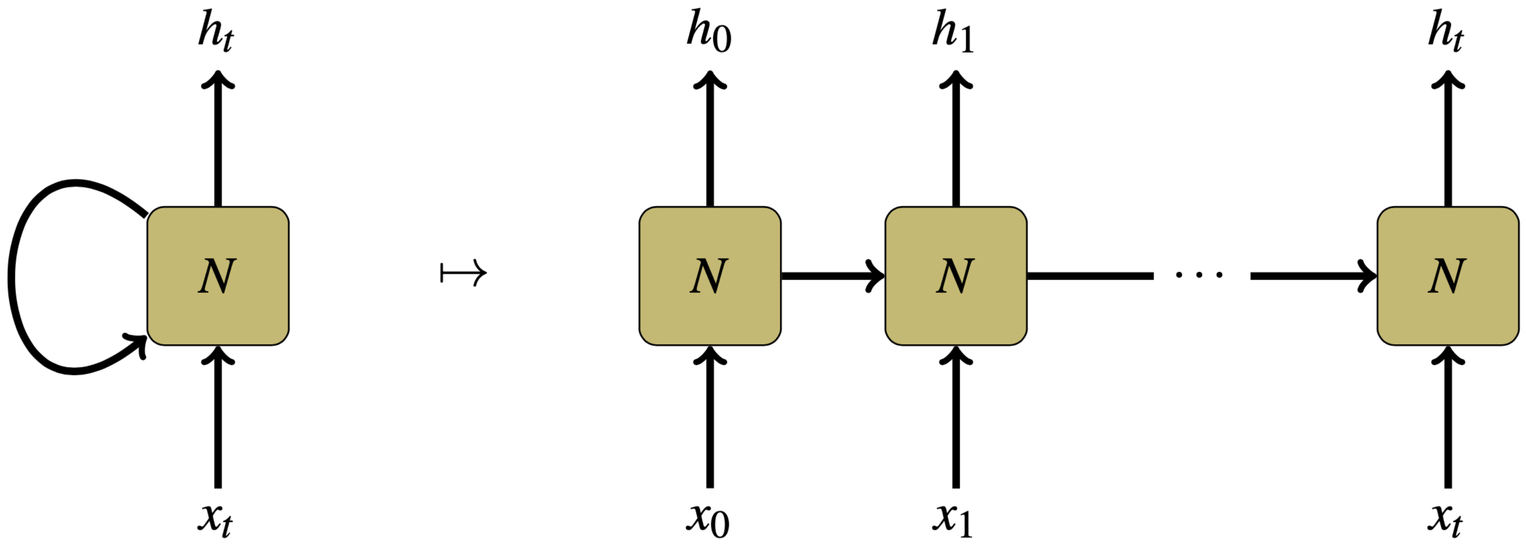
Selectional Restrictions

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

Selectional Restrictions

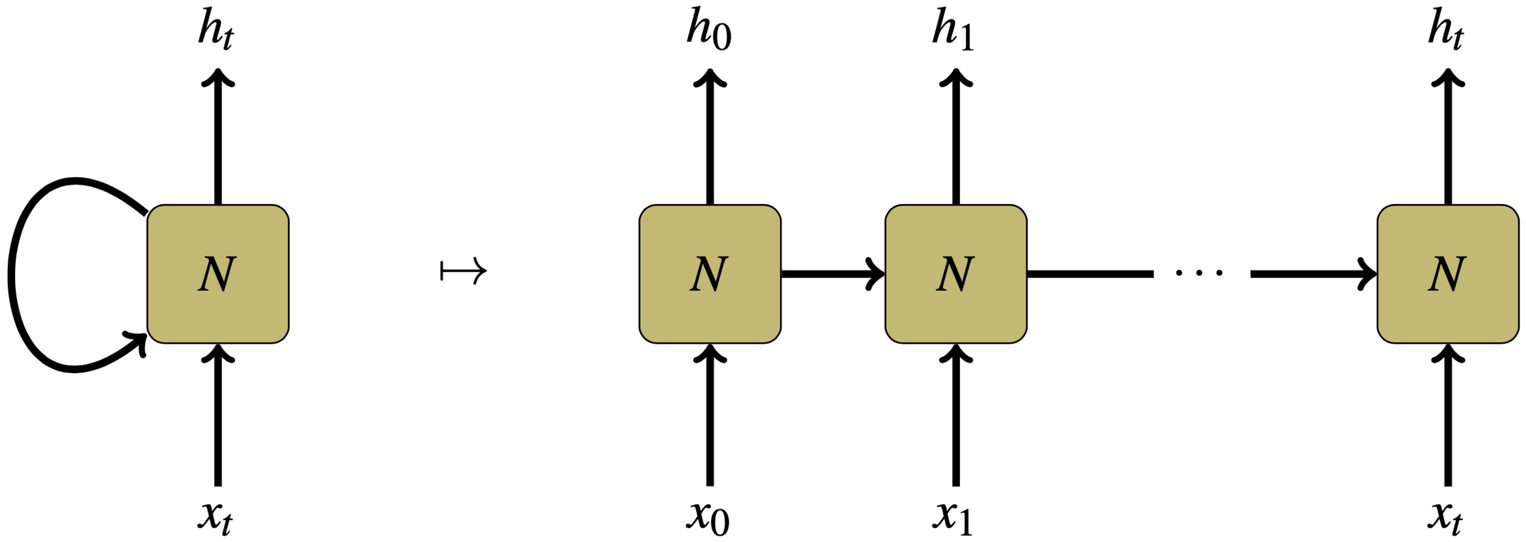
- The **family** moved from the city because they wanted a larger **house**.
- The **team** moved from the city because they wanted a larger **market**.
- Need models that can capture long-range dependencies like this.
- N-gram (whether count-based or neural) **cannot** (e.g. with n=4)
  - P(word | “they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

RNNs



Steinert-Threlkeld and Szymanik 2019; Olah 2015

RNNs



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

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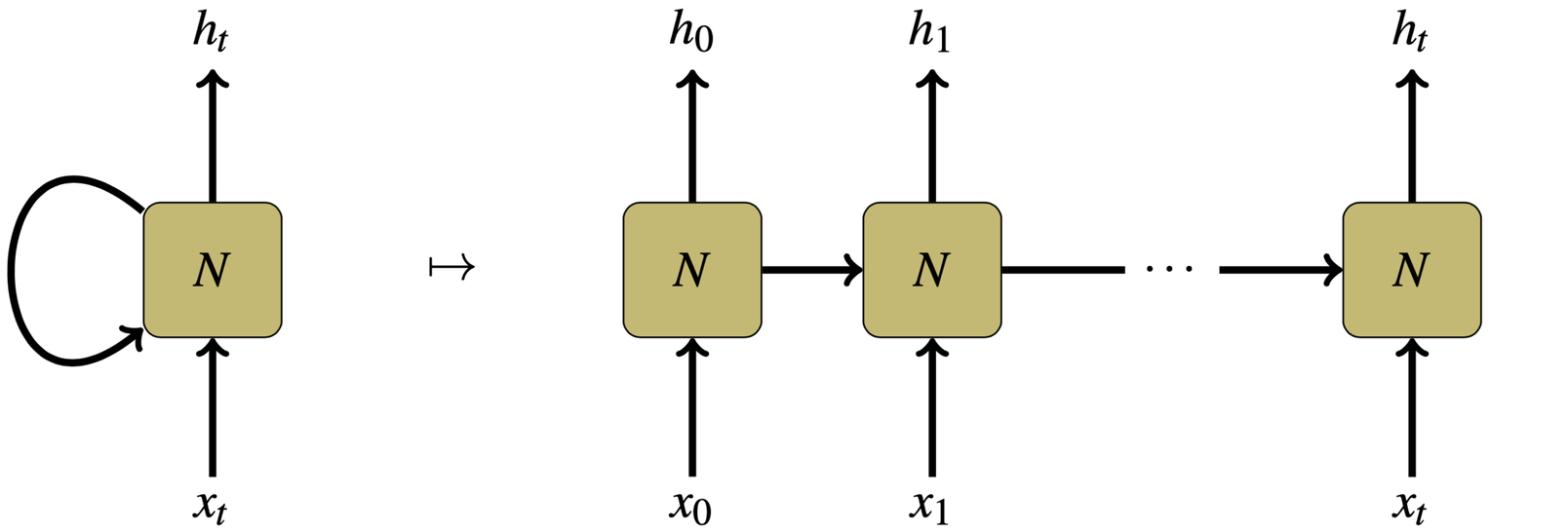
RNNs



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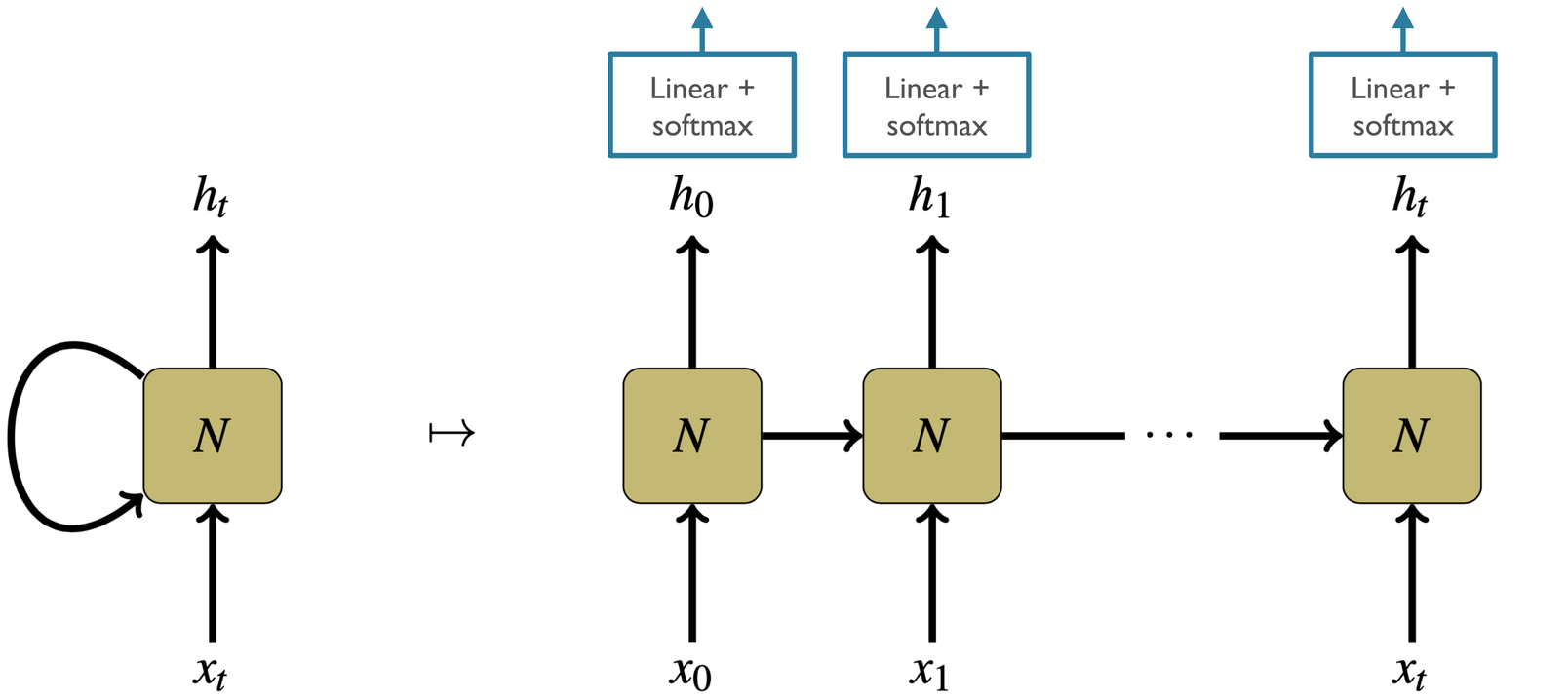
RNNs



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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*
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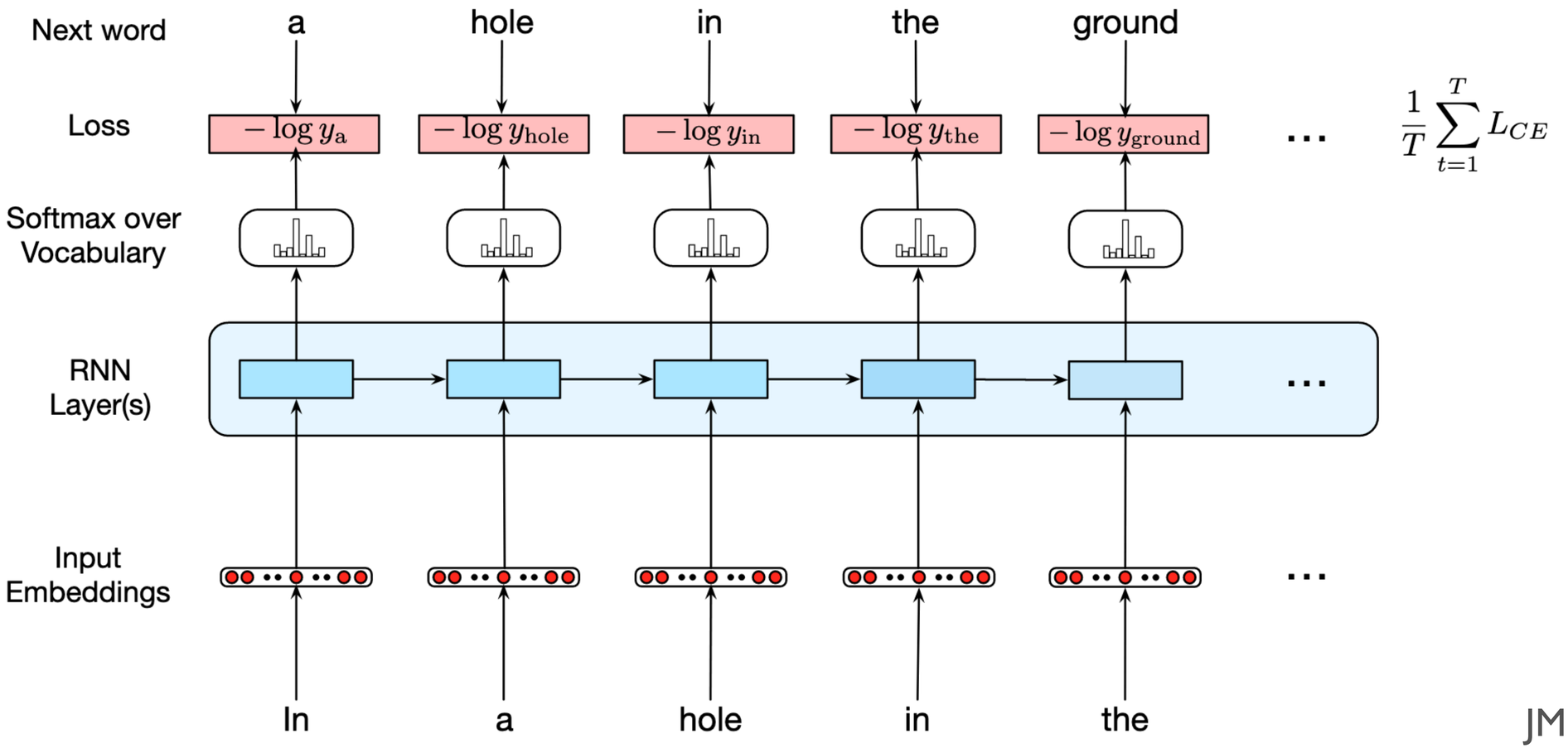
Simple/"Vanilla" RNN:

$$h_t = \tanh(W_x x_t + W_h h_{t-1} + b)$$

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

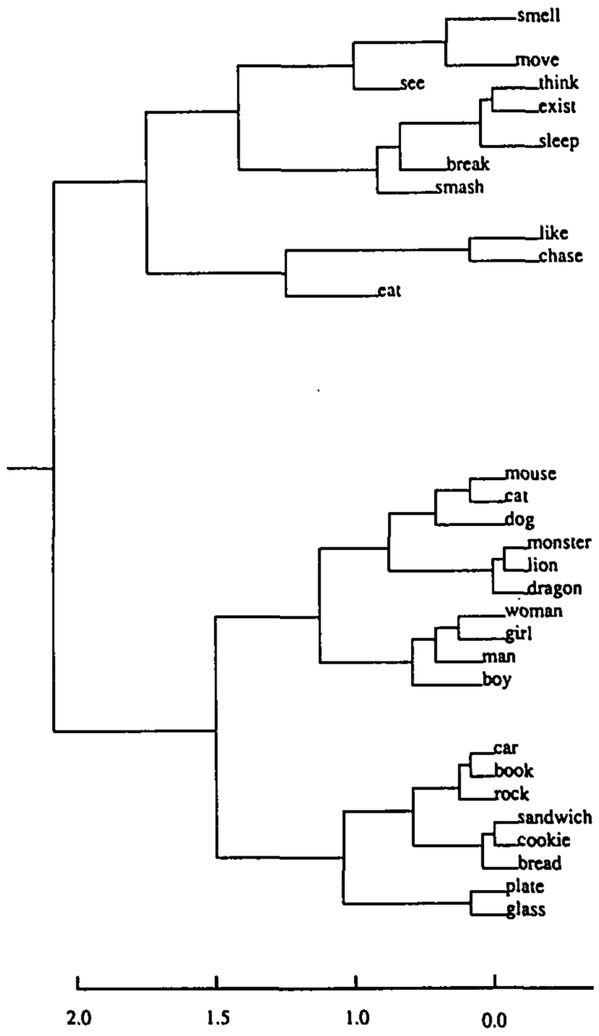


$$\frac{1}{T}\sum_{t=1}^{T} L_{CE}$$

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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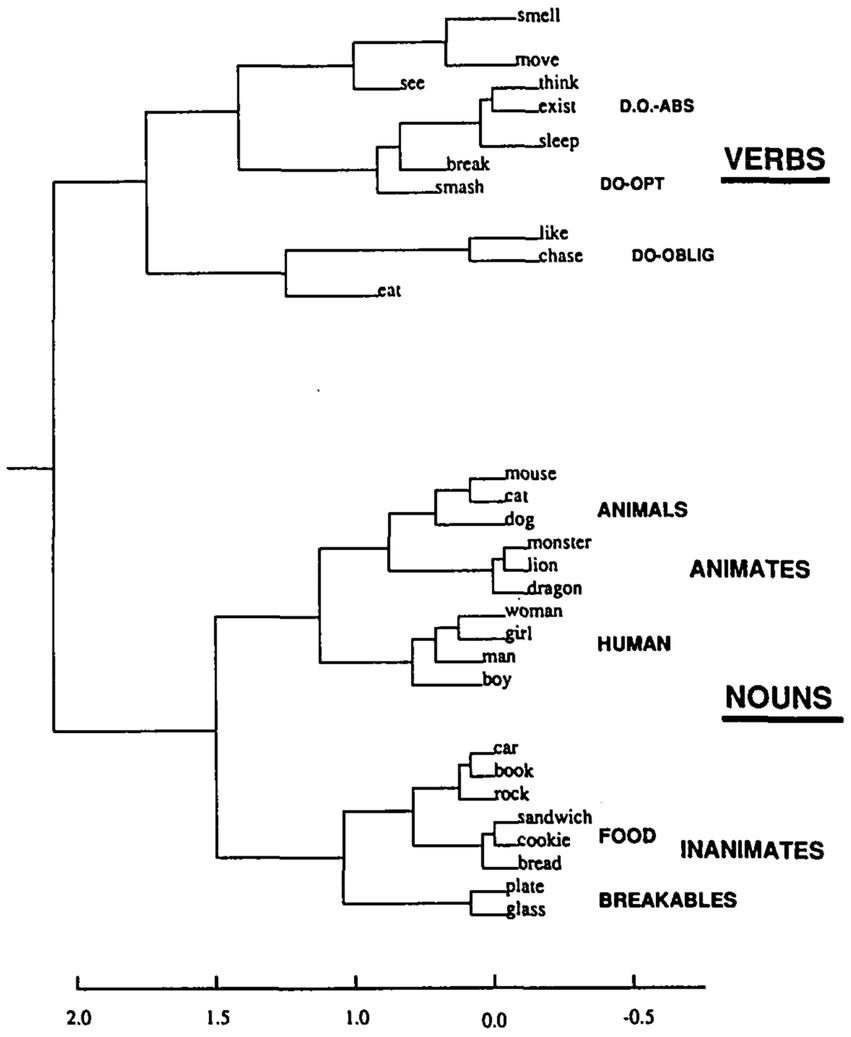
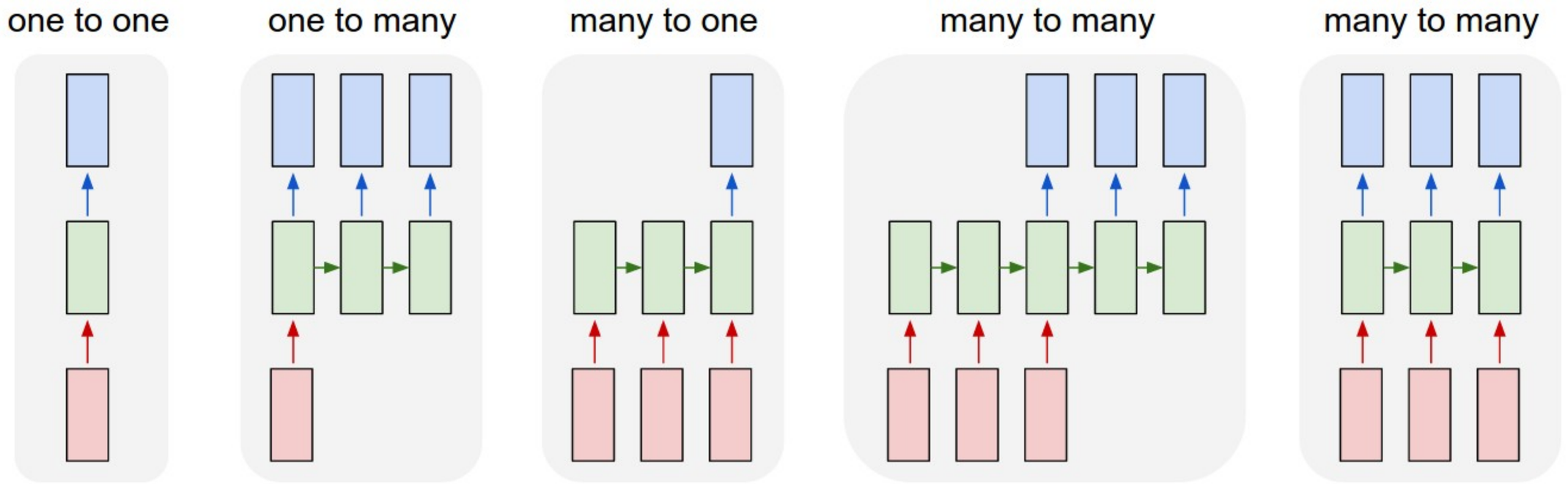


Elman 1990

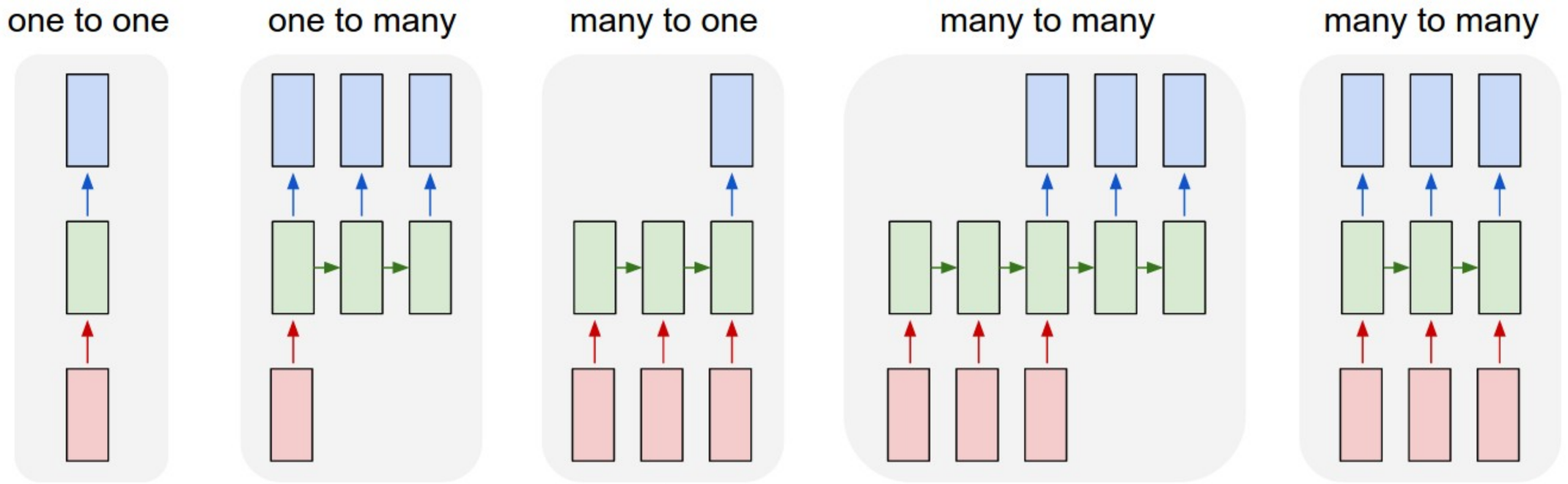
Using RNNs



MLP

e.g. image captioning

Using RNNs



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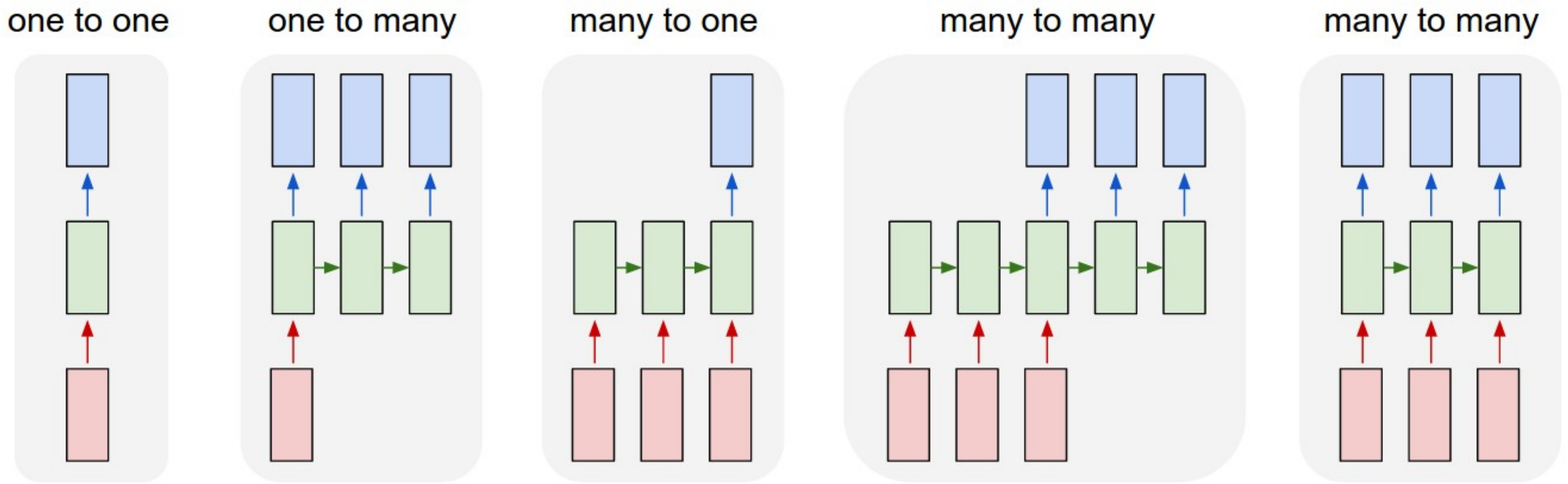
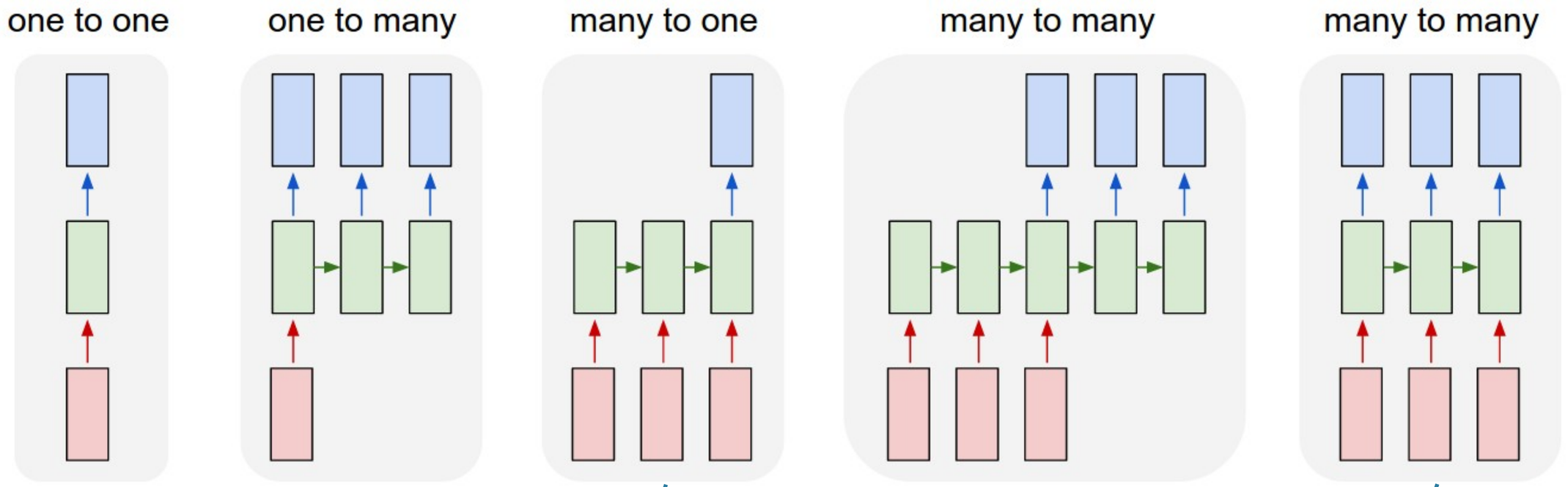
Using RNNs


one to one
one to many
many to one
many to many
many to many
MLP
e.g. image captioning
e.g. text classification
e.g. POS tagging

Using RNNs



MLP

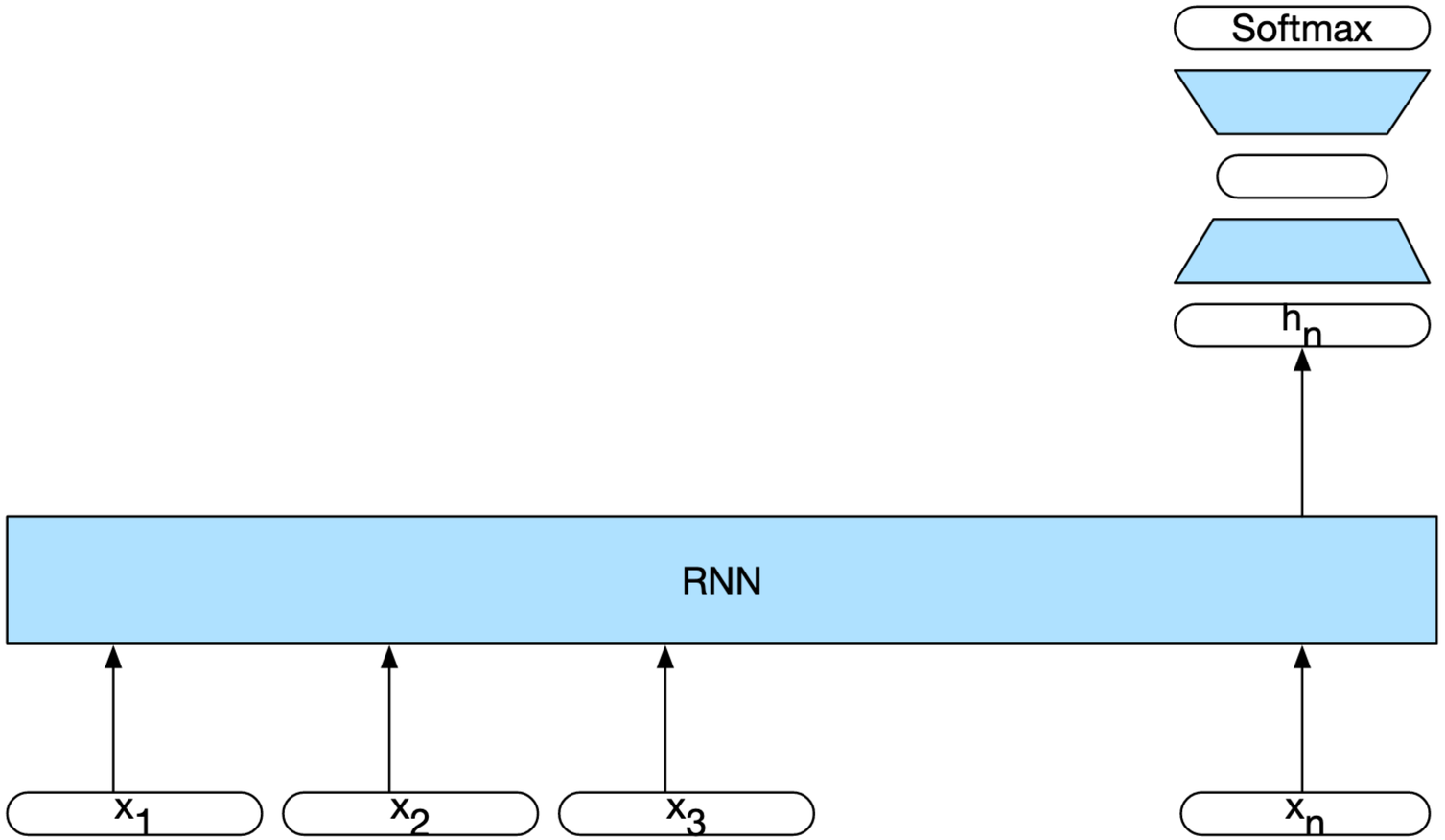
e.g. image captioning

e.g. text classification

seq2seq (later)

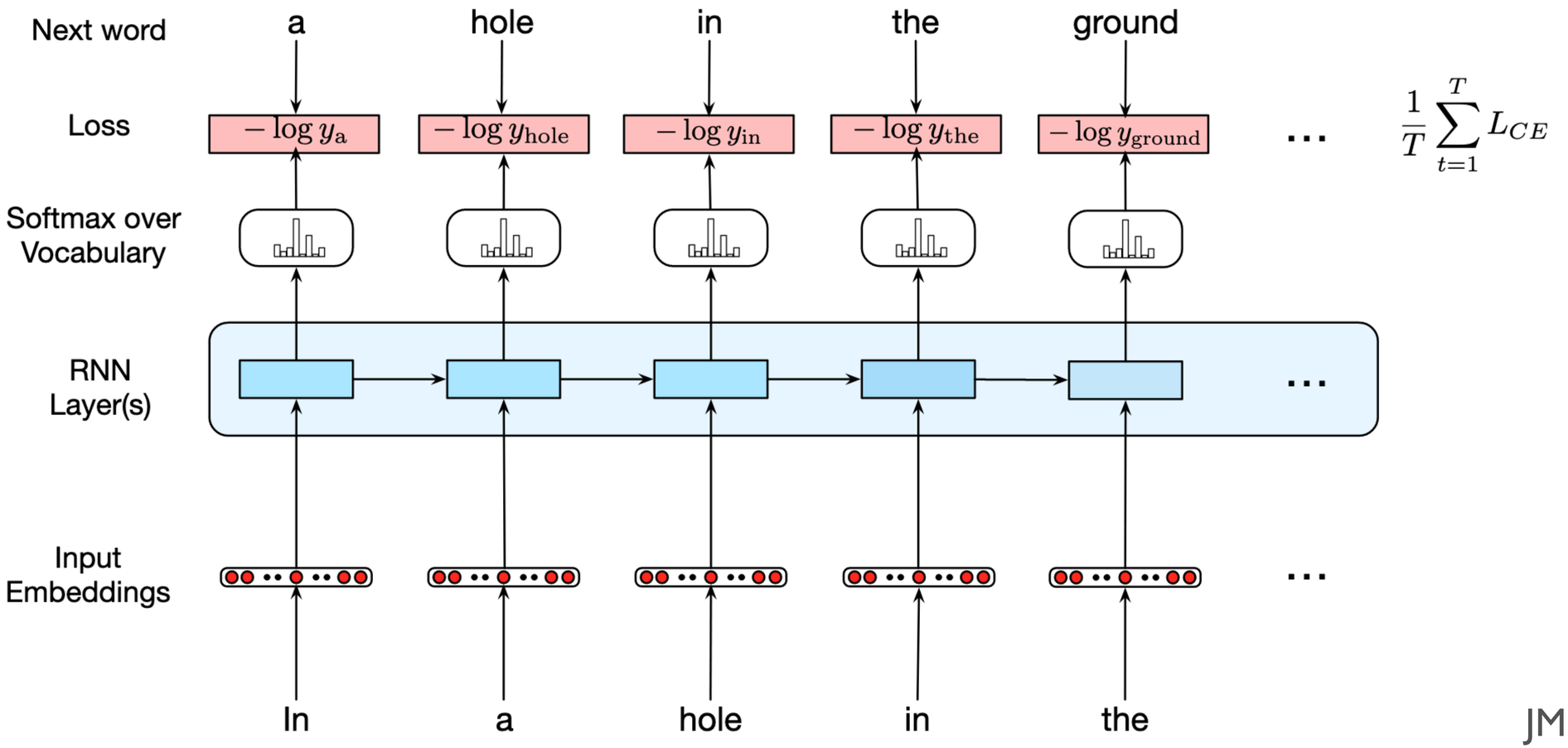
e.g. POS tagging

RNN for Text Classification



JM sec 9.2.5

RNNs for Language Modeling



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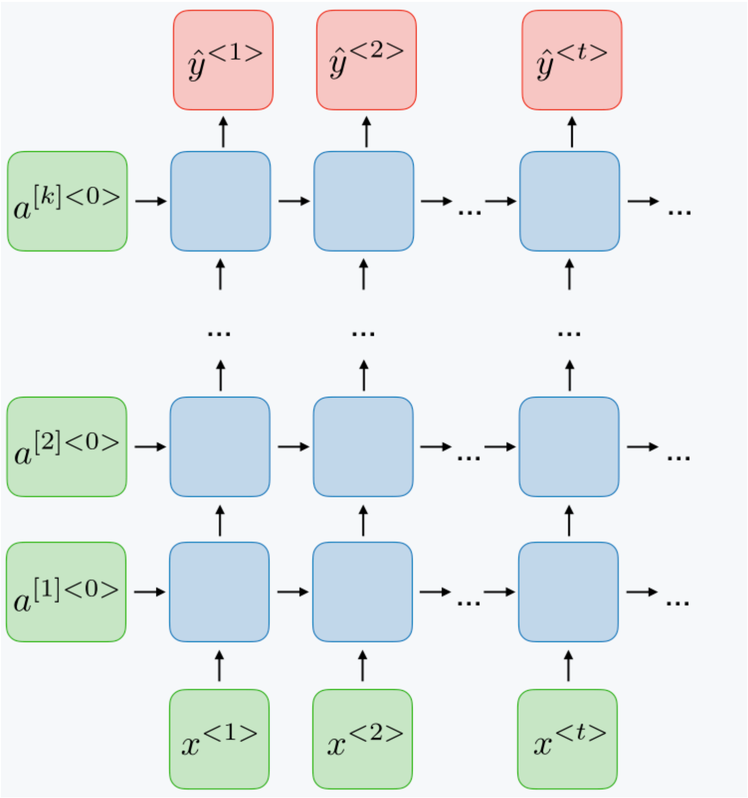
Two Extensions

- Deep RNNs:



Source: RNN cheat sheet

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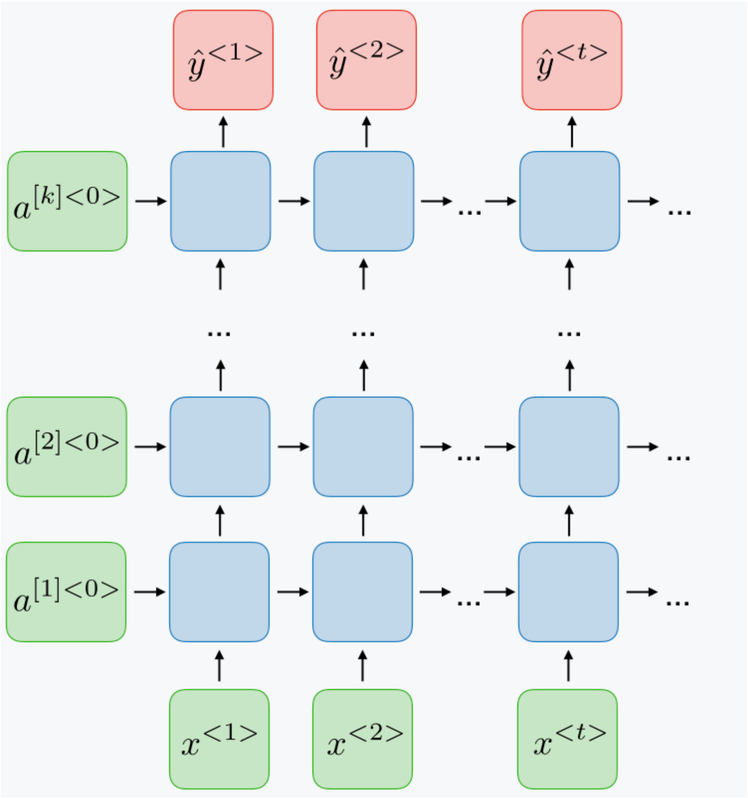
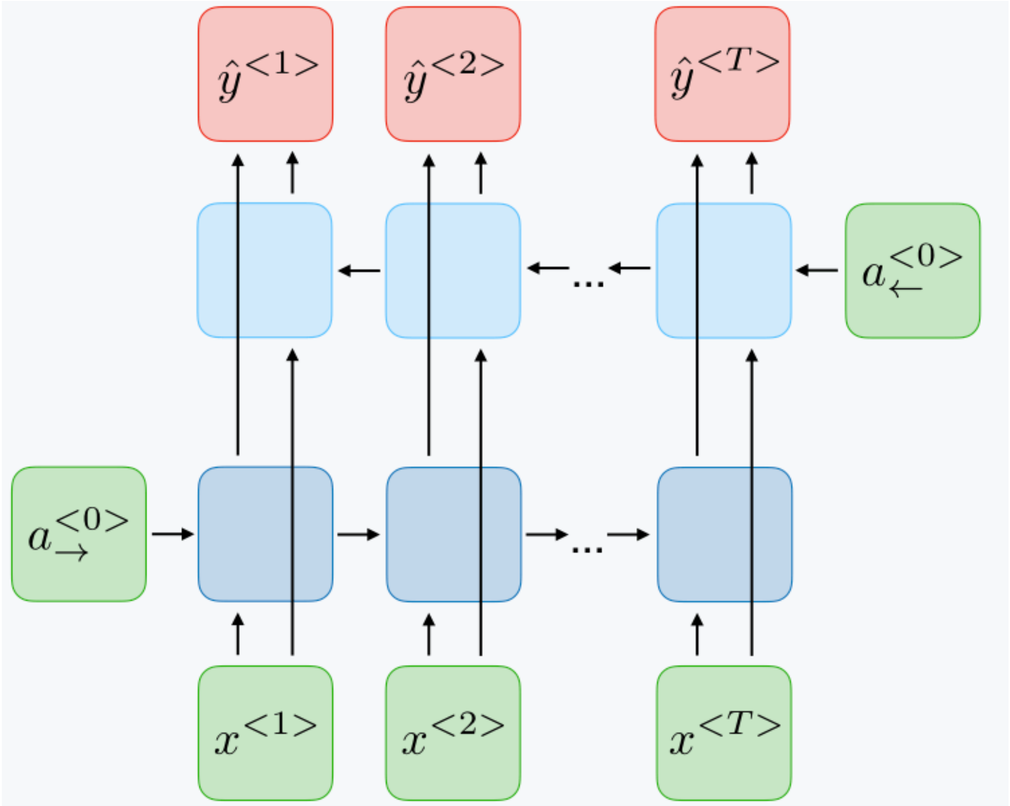


- Bidirectional RNNs:



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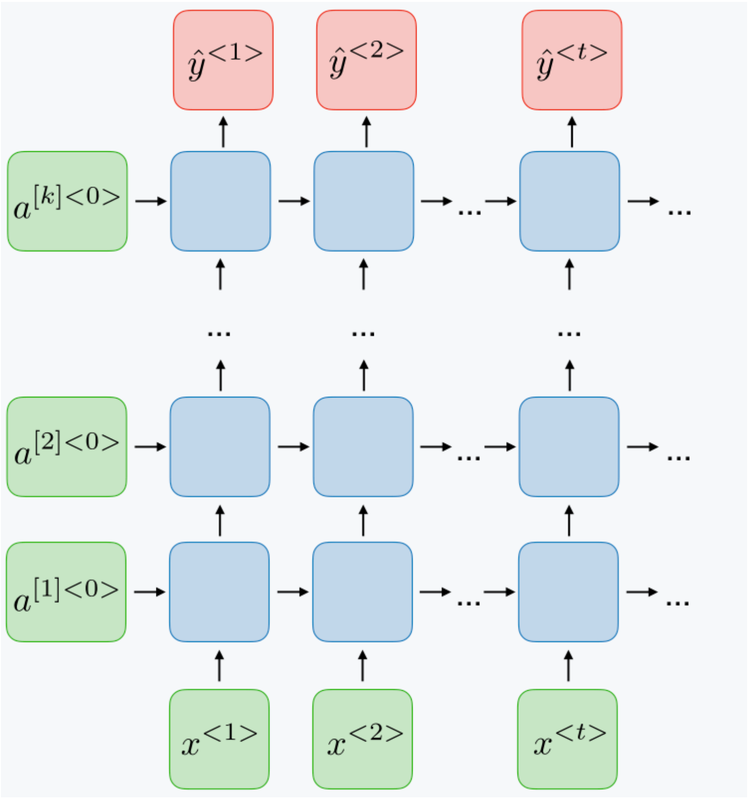

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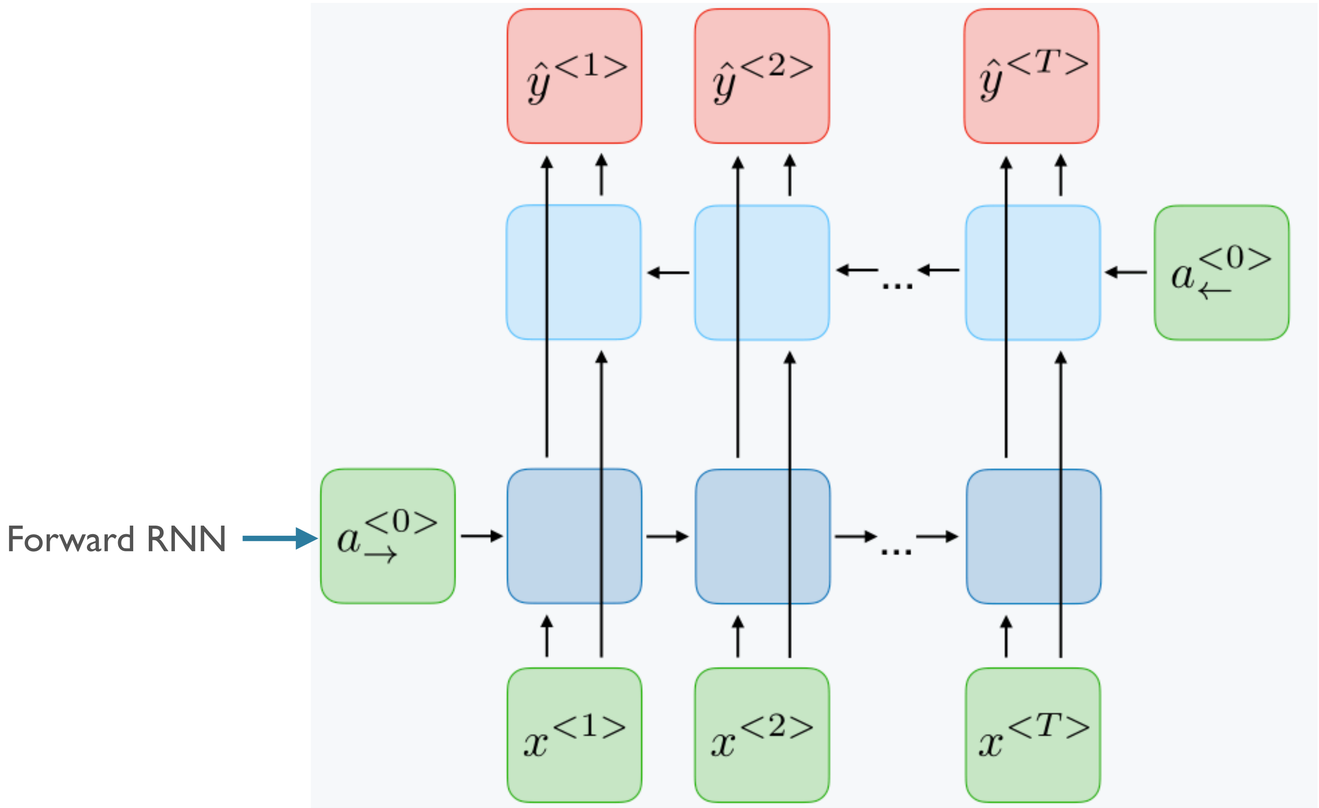

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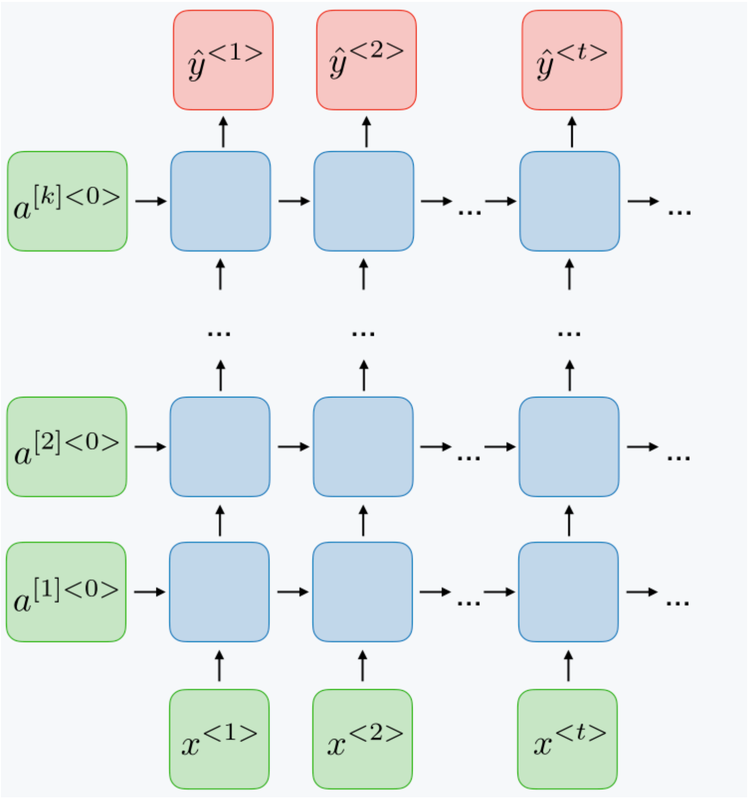

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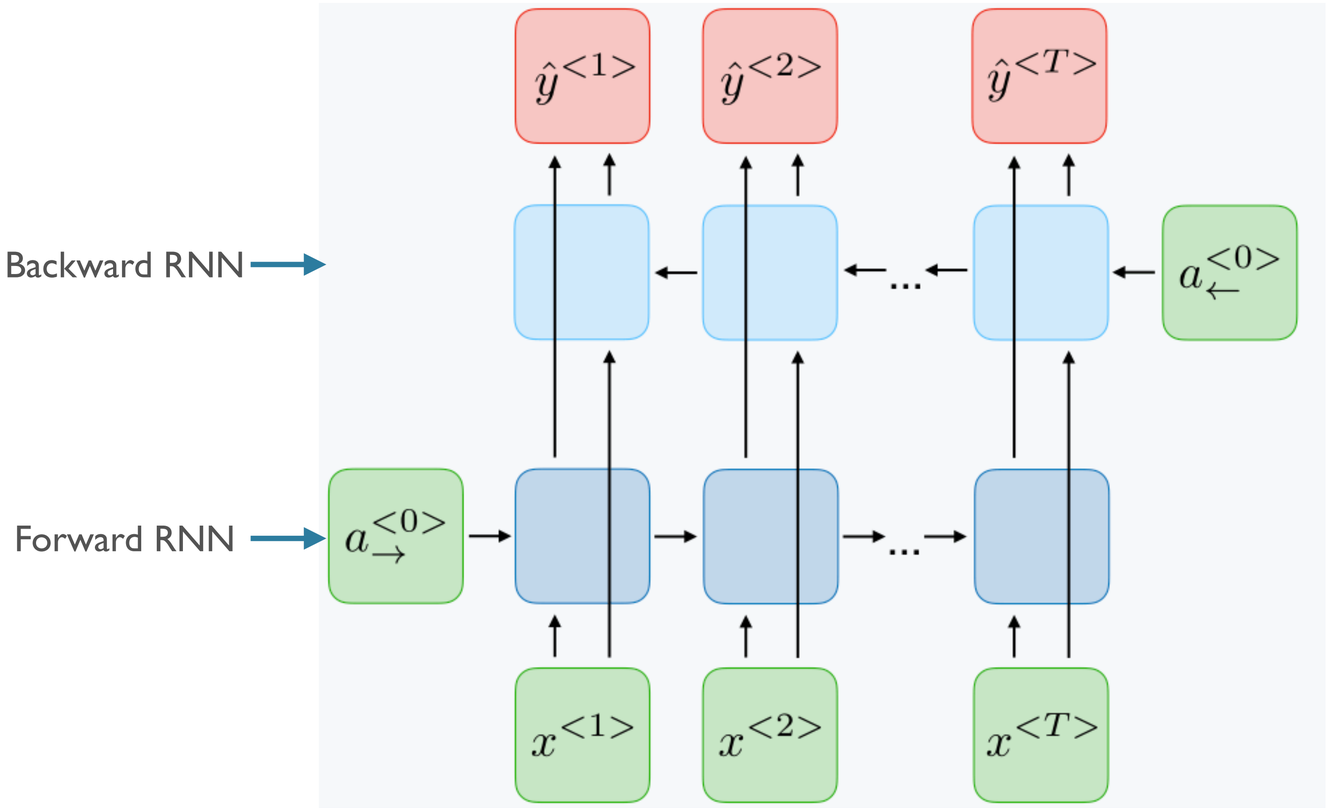

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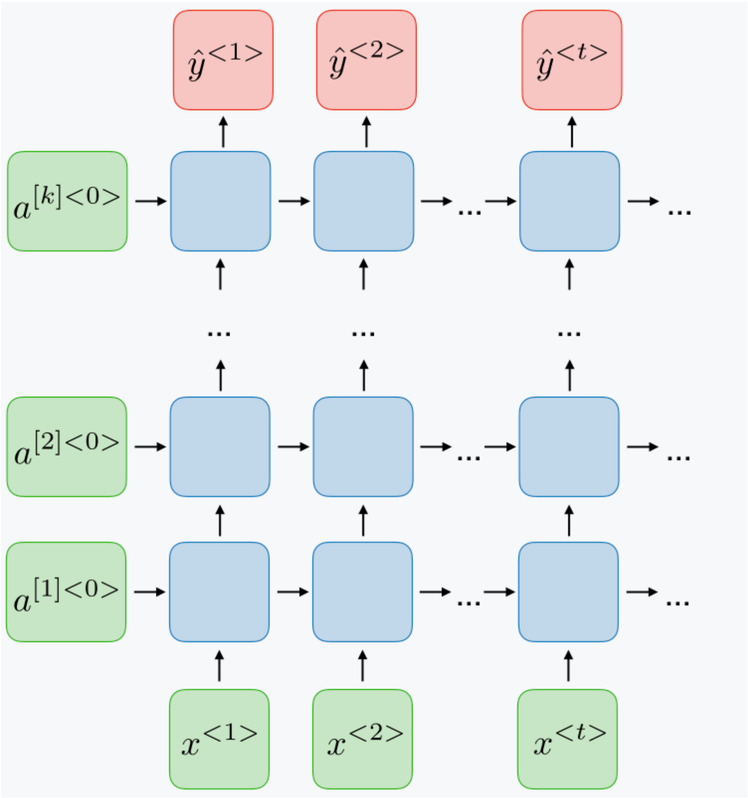

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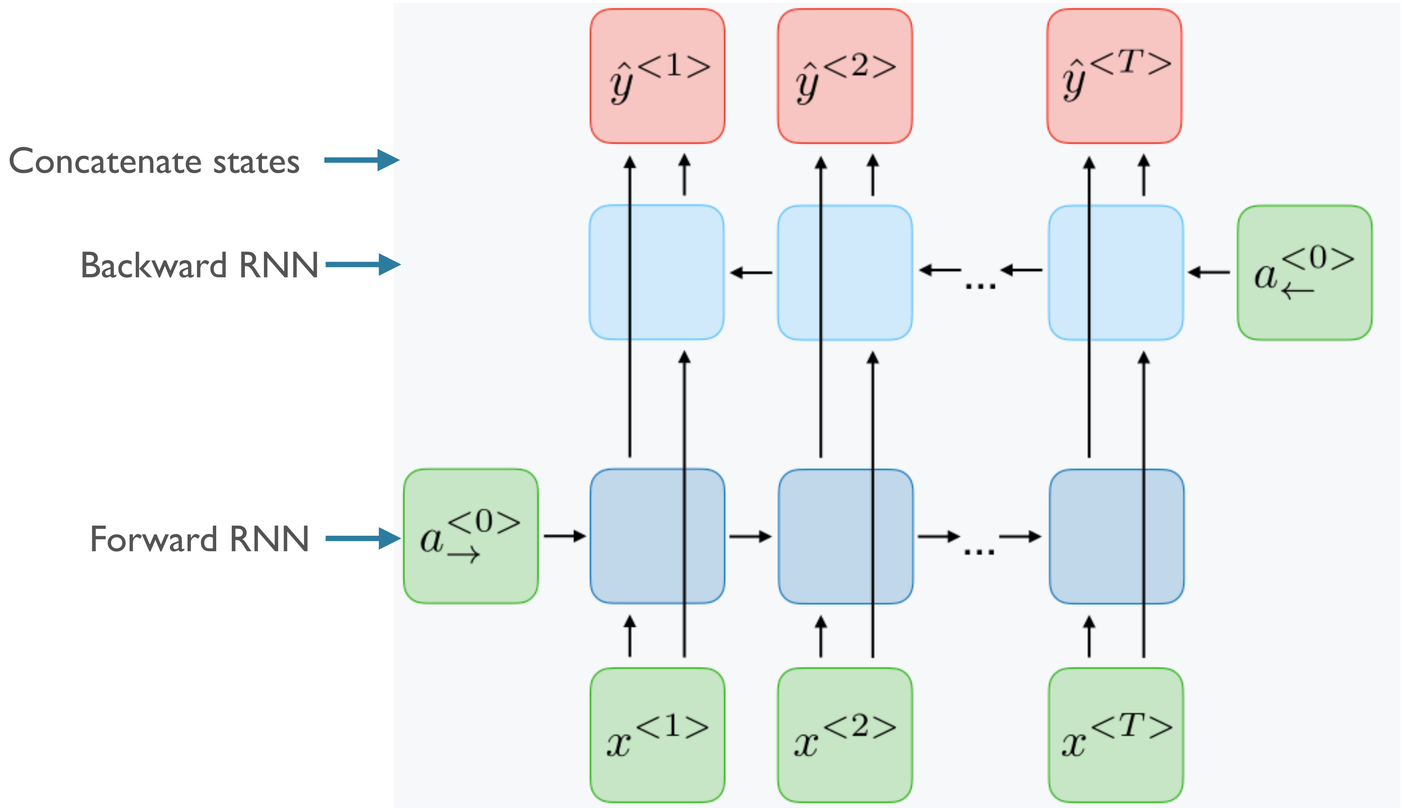

Source: RNN cheat sheet

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