RNN Language Modeling & Introduction to Prompt Engineering

CS 780/880 Natural Language Processing Lecture 17

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Last lecture

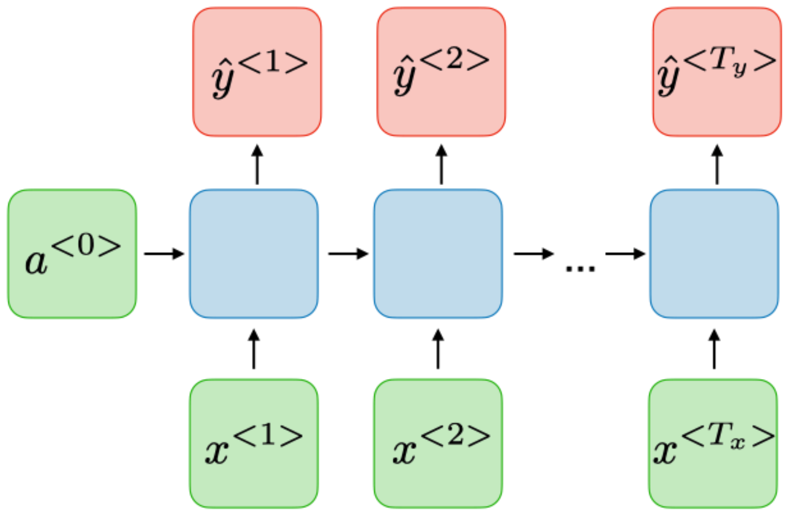
Sequence tagging

- POS tagging

LSTMs as a NLP Swiss army knife

Domain-specific word embeddings

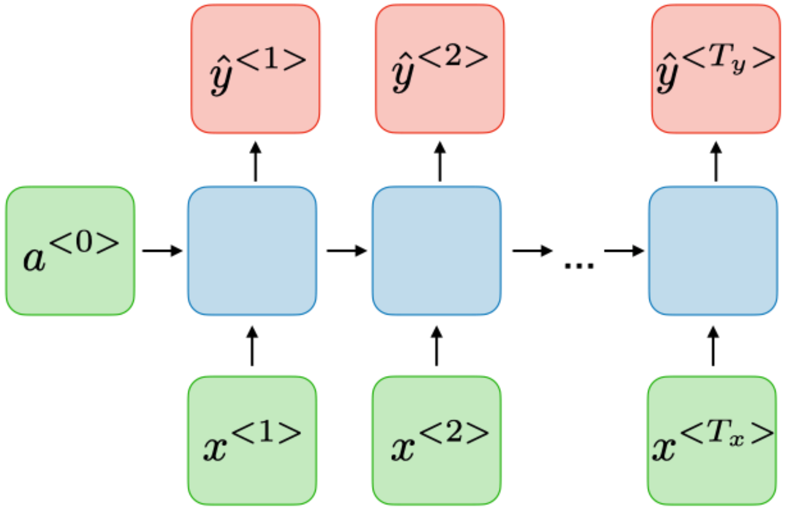
Masked loss



LSTMs: NLP Swiss army knife

LSTMs are exciting for us because they are the Swiss army knife of NLP models.

- Sequence classification
- Sequence tagging
- **Language modeling**
- Text-to-text (e.g. translation)



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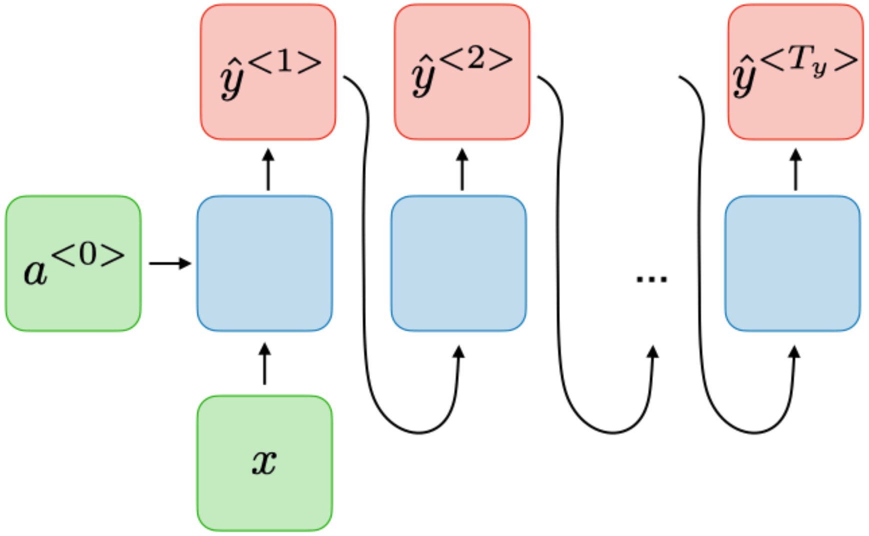


Review: Language modeling

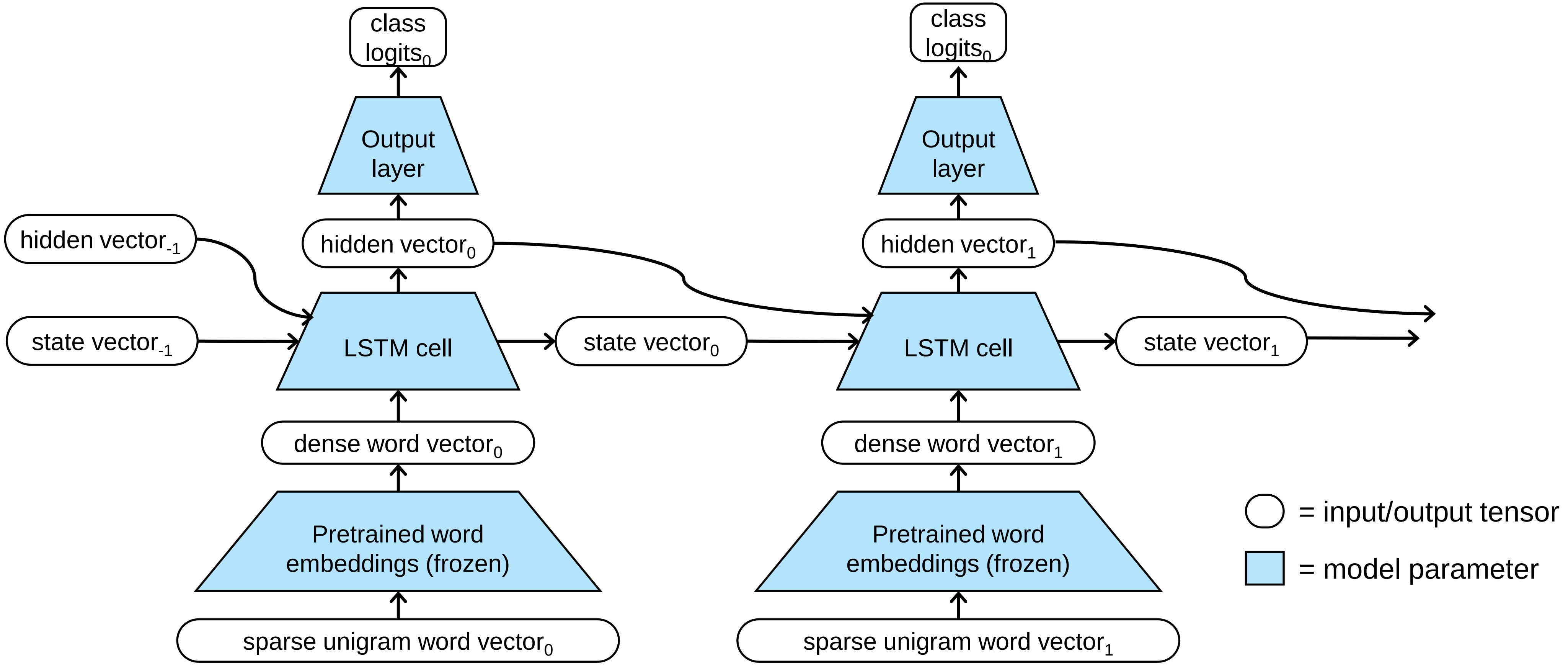
Basic idea: Given words $\{w^0, w^1, w^2, \ldots, w^{t-1}\}$, we want to be able to reliably predict w^t

If we can do this, we can:

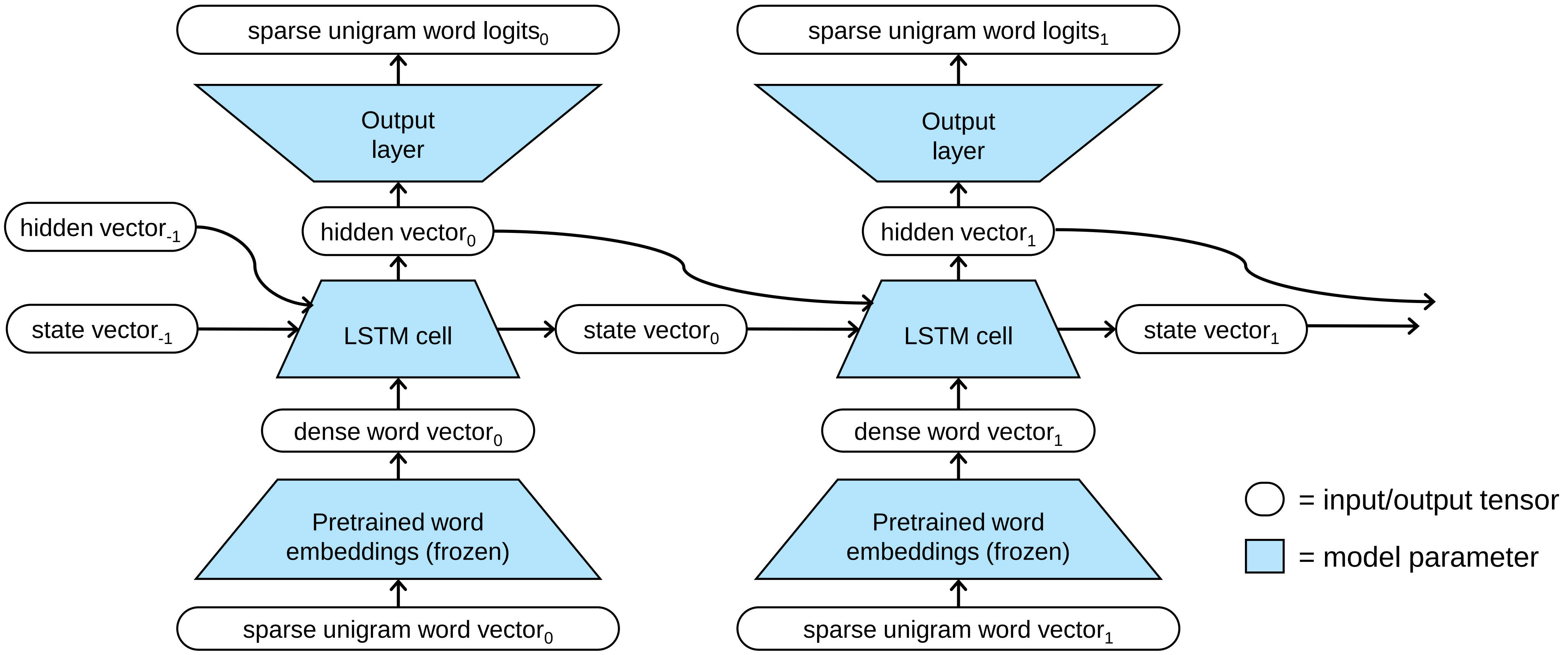
- Generate new text
- Assess the overall likelihood of a piece of text
- (In 2023) talk to the model like it is a person and make it do stuff for us
  - Prompt engineering

https://courses.engr.illinois.edu/cs447/fa2020/index.html

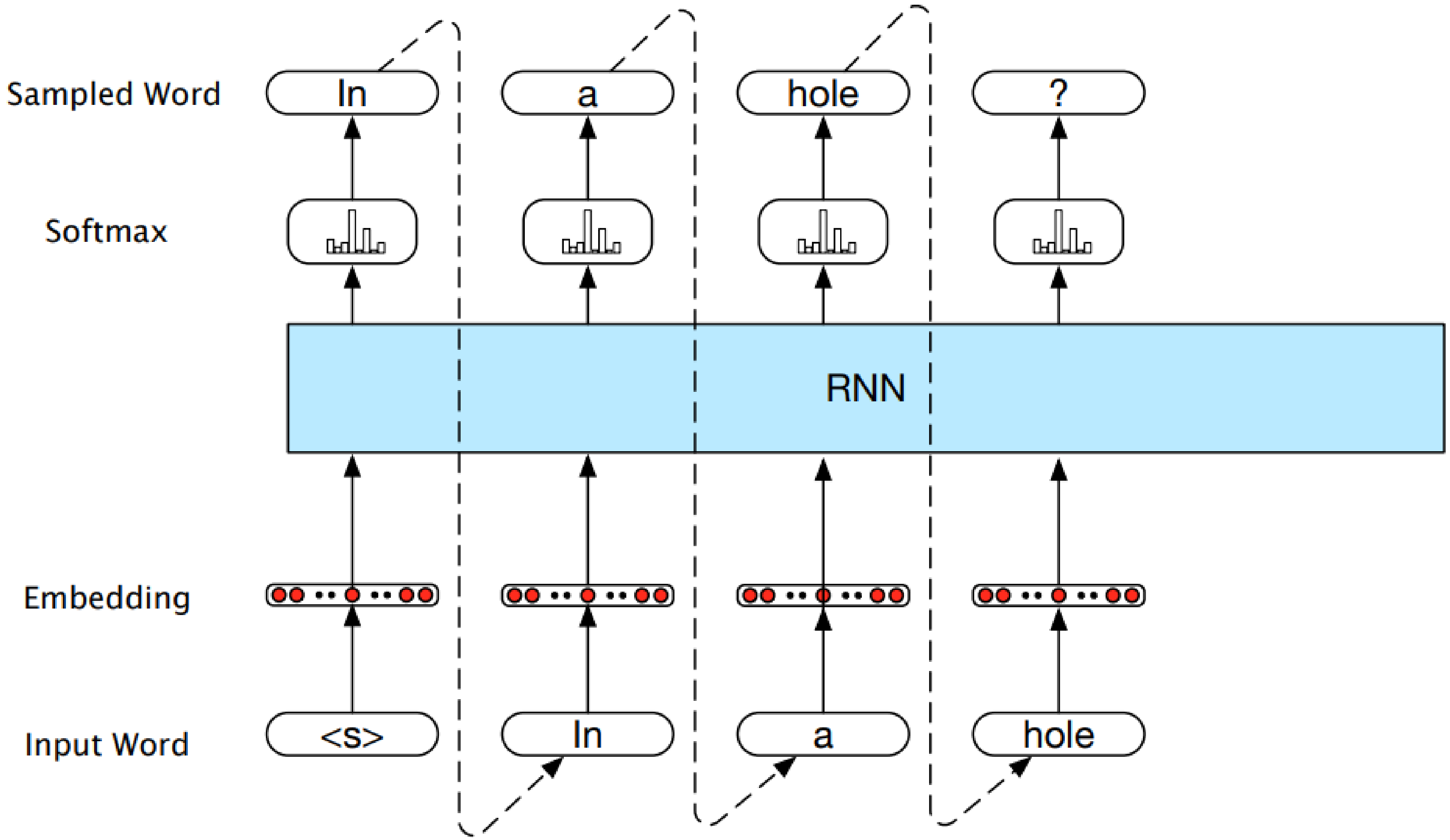
Another view of sequence tagging



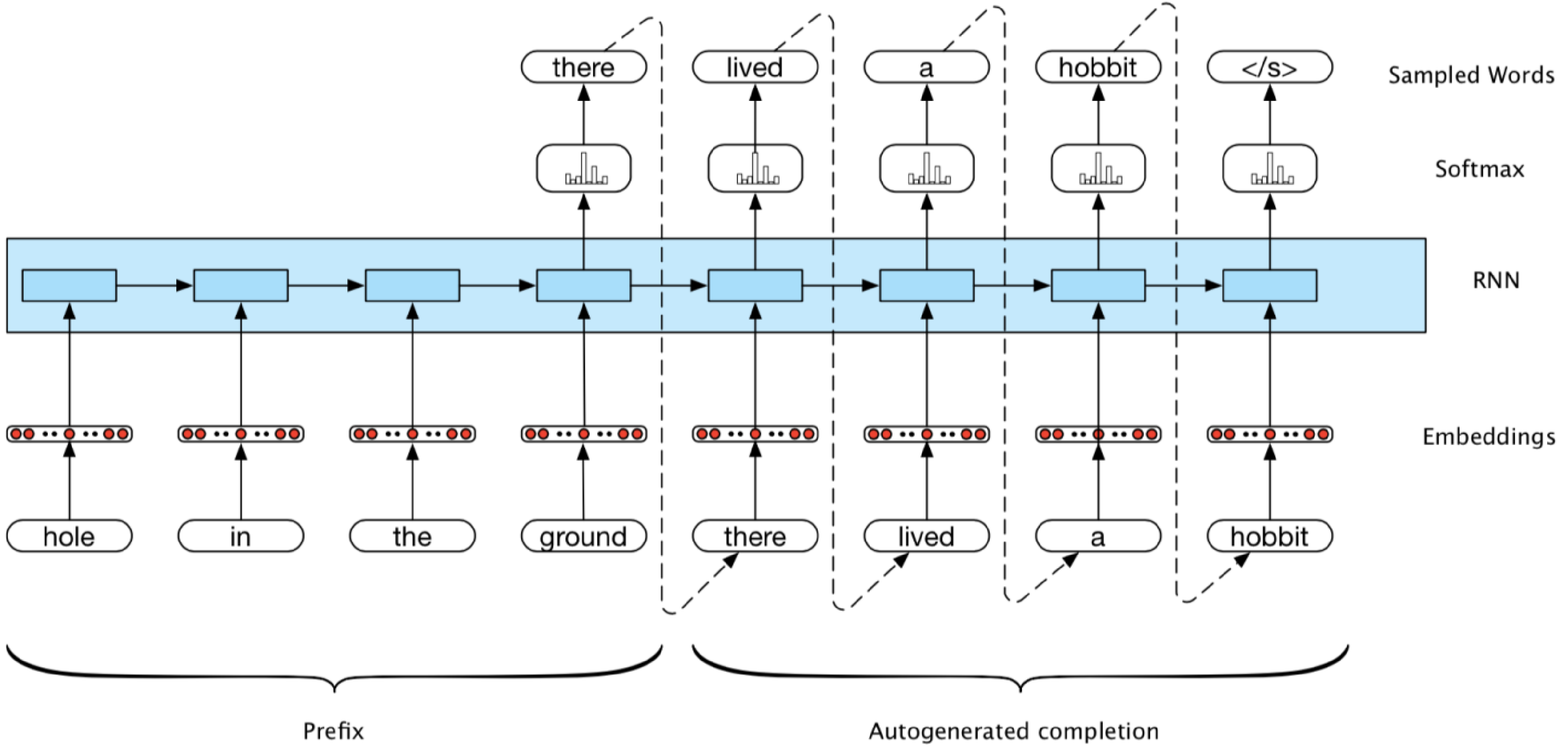
Word logits rather than class logits



Autoregressive generation



Autoregressive completion



Generating with a RNN

Also known as **decoding**: taking the output hidden-state vectors from the RNN at each step and decoding them into a sequence of actual words

Greedy decoding: always pick the most likely word at any given step

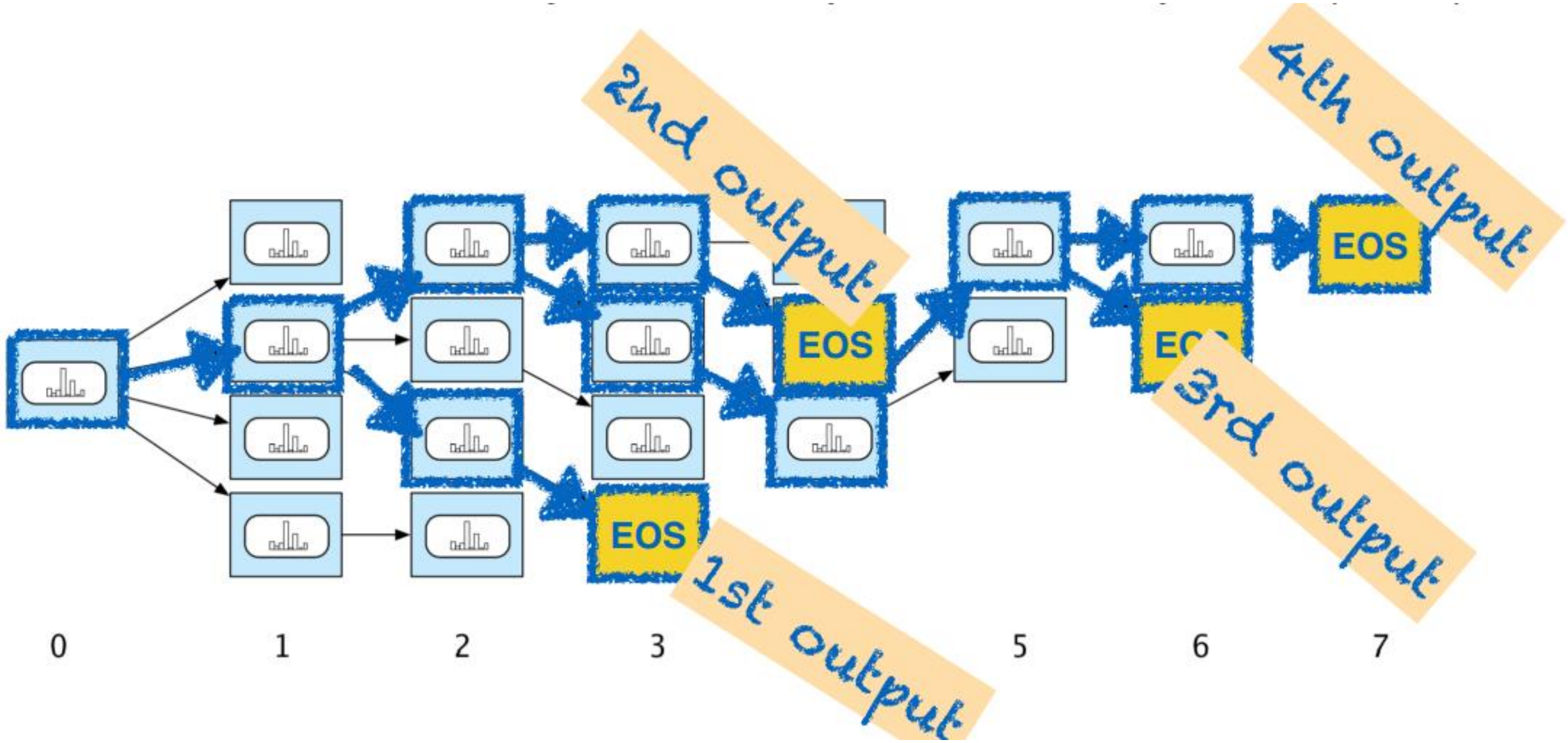
Sampling: randomly sample each word according to output logits

Beam search decoding: keep a number of possible sequences after each time step

- **Fixed-width beam**: keep top-K sequences
- **Variable-width beam**: keep all sequences whose likelihood is within certain threshold of best

Beam search decoding

- Keep the k best options around at each time step.
- Operate breadth-first: keep the k best next hypotheses among the best continuations for each of the current k hypotheses.
- Reduce beam width every time a sequence is completed (EOS)



Training RNN language models

Maximum likelihood estimation (MLE):

Given training samples $w^{(1)}w^{(2)}\ldots w^{(T)}$, find the parameters θ^* that assign **the largest probability to these training samples:**

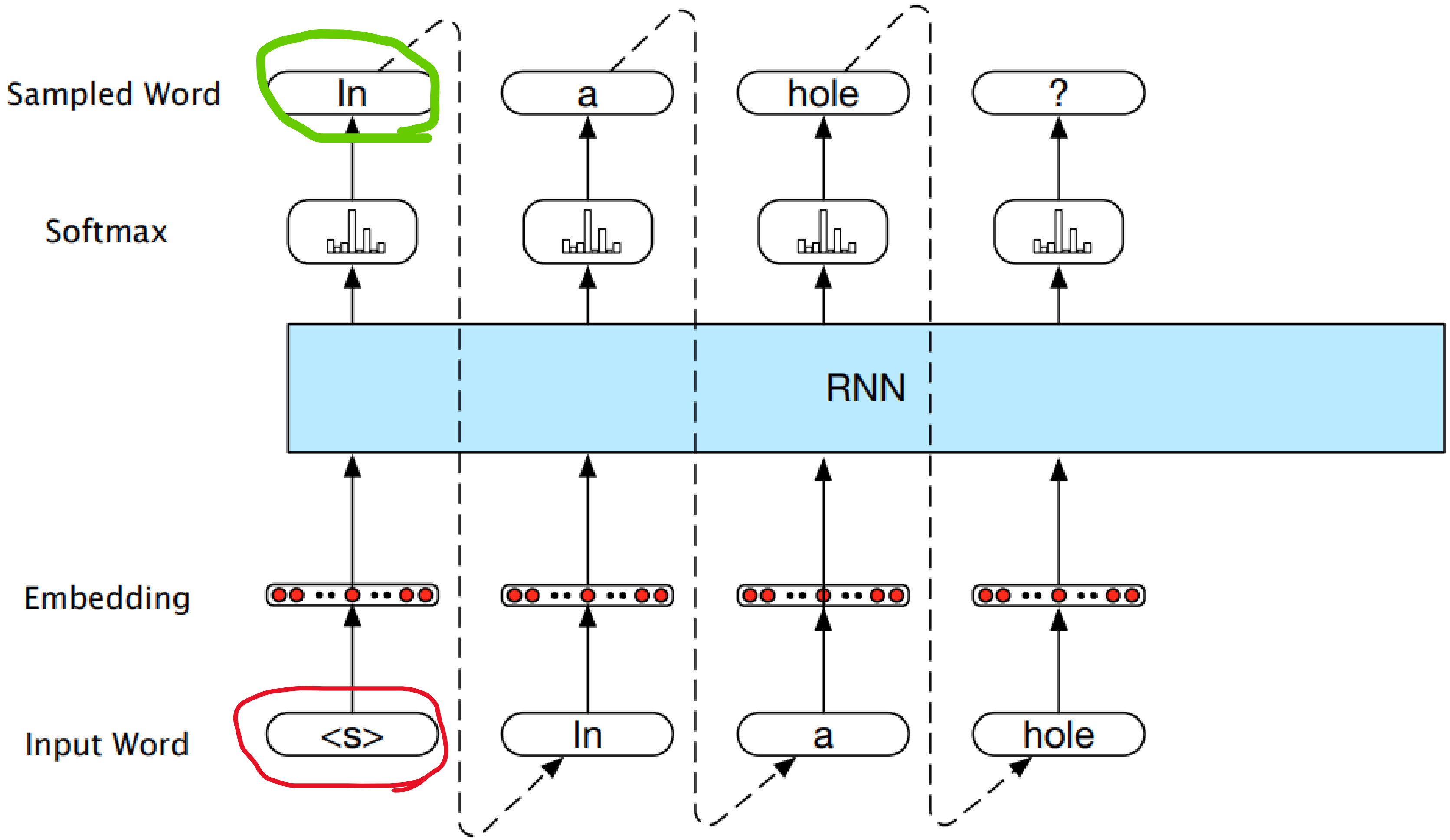
$$\theta^* = \mathrm{argmax}_\theta P_\theta(w^{(1)}w^{(2)}\ldots w^{(T)}) = \mathrm{argmax}_\theta \prod_{t=1..T} P_\theta(w^{(t)} \mid w^{(1)}\ldots w^{(t-1)})$$

- Aka "teacher forcing"

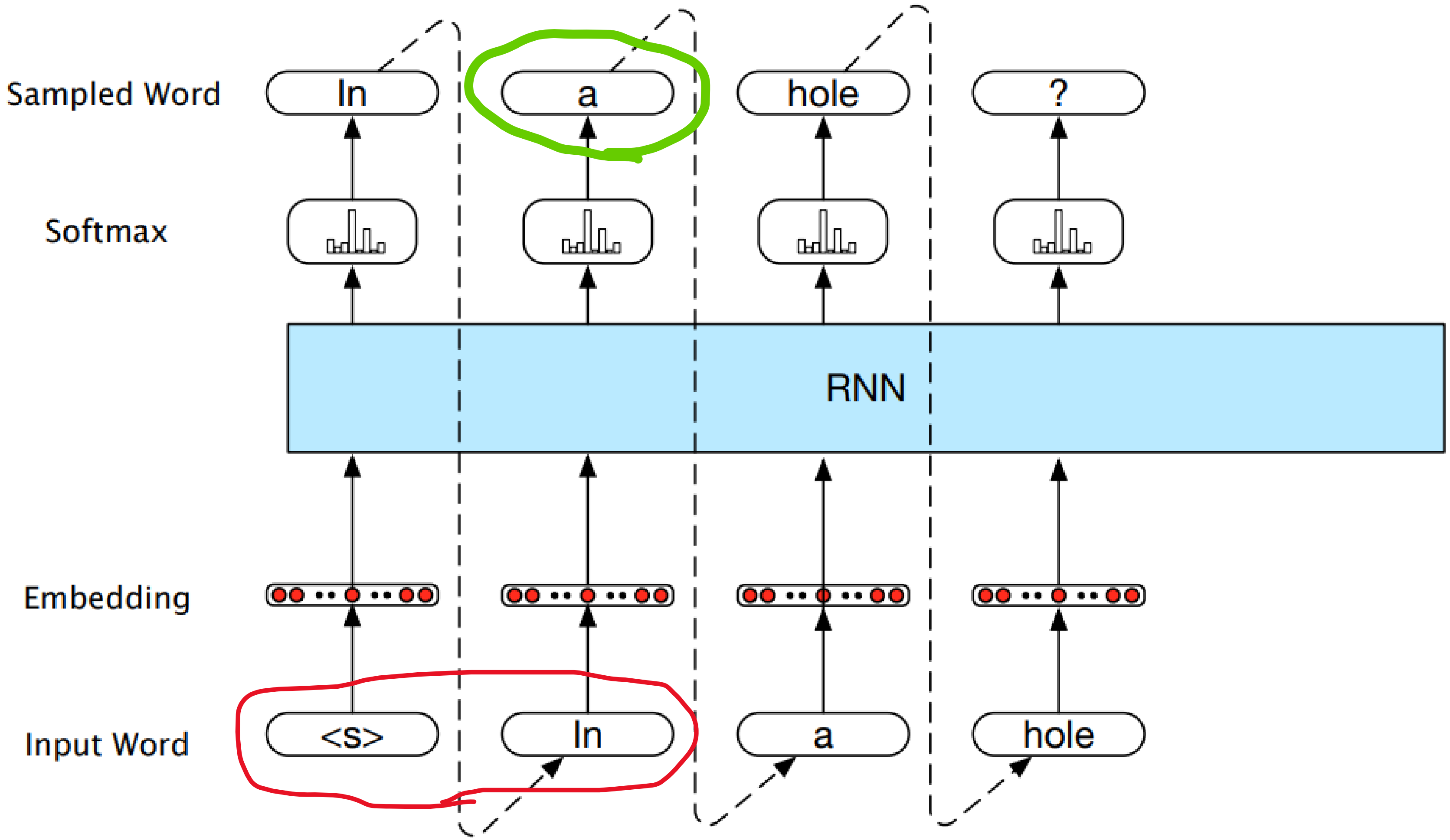
Each training sequence $\{w^0, w^1, w^2, \ldots, w^T\}$ turns into T training items:

Given $\{w^0, w^1, w^2, \ldots, w^{t-1}\}$, train model to maximize probability of w^t

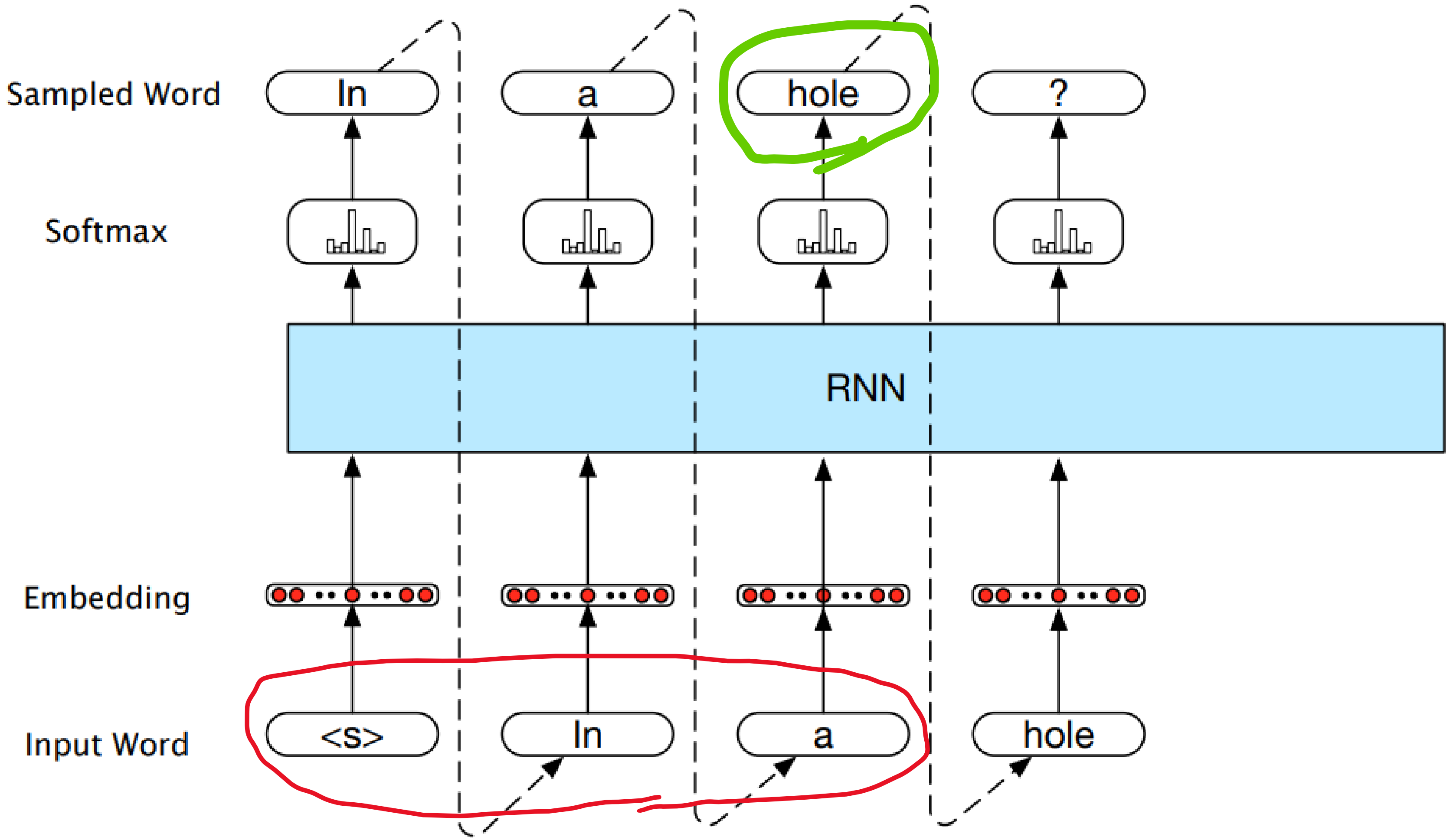
Maximum likelihood estimation



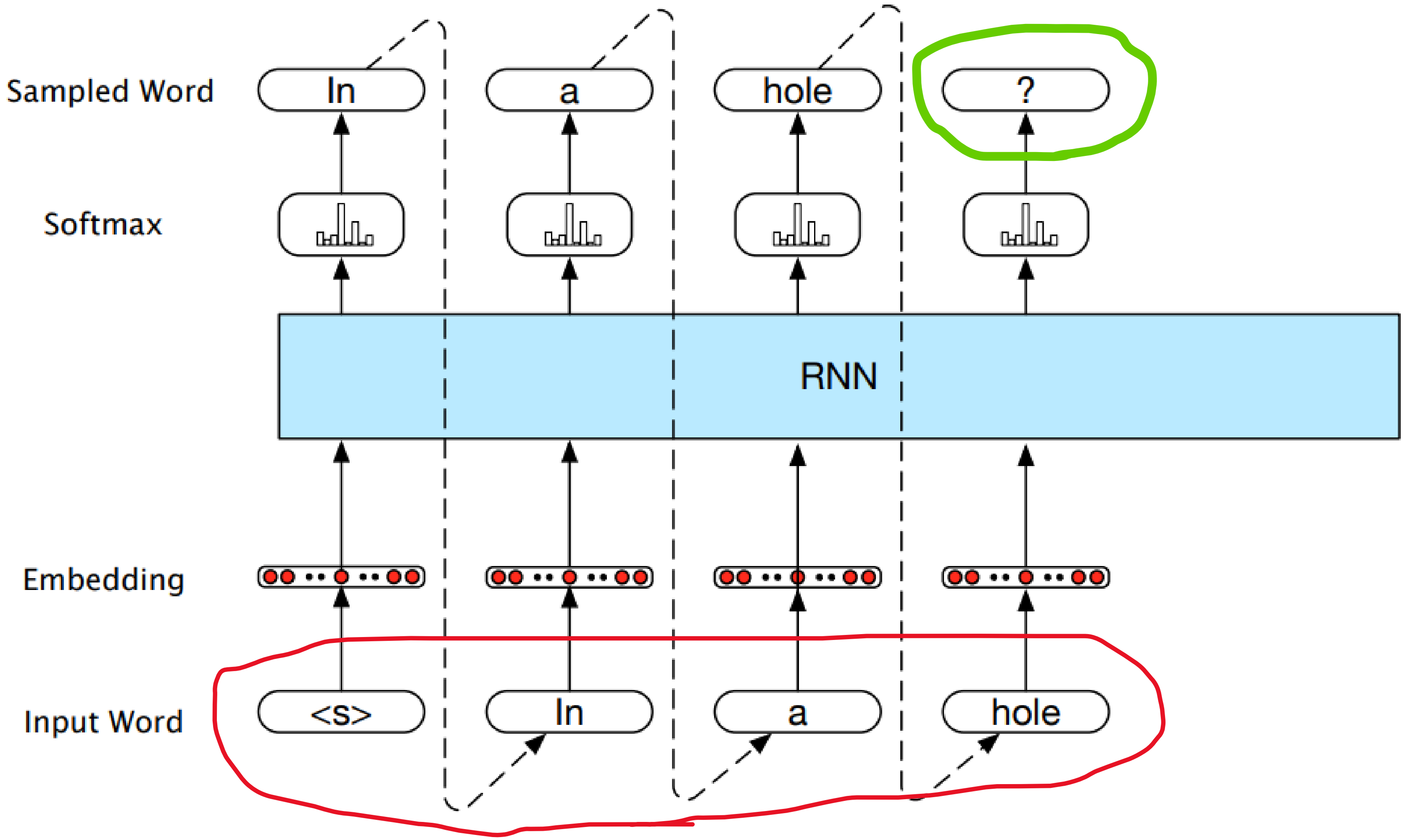
Autoregressive generation



Autoregressive generation



Autoregressive generation



Problem with teacher forcing

Neural networks (and ML models generally) don't do well with **domain shift**

Meaning, if you train the model on data that is distributed one way, it generally will not do well on data that is distributed a different way.

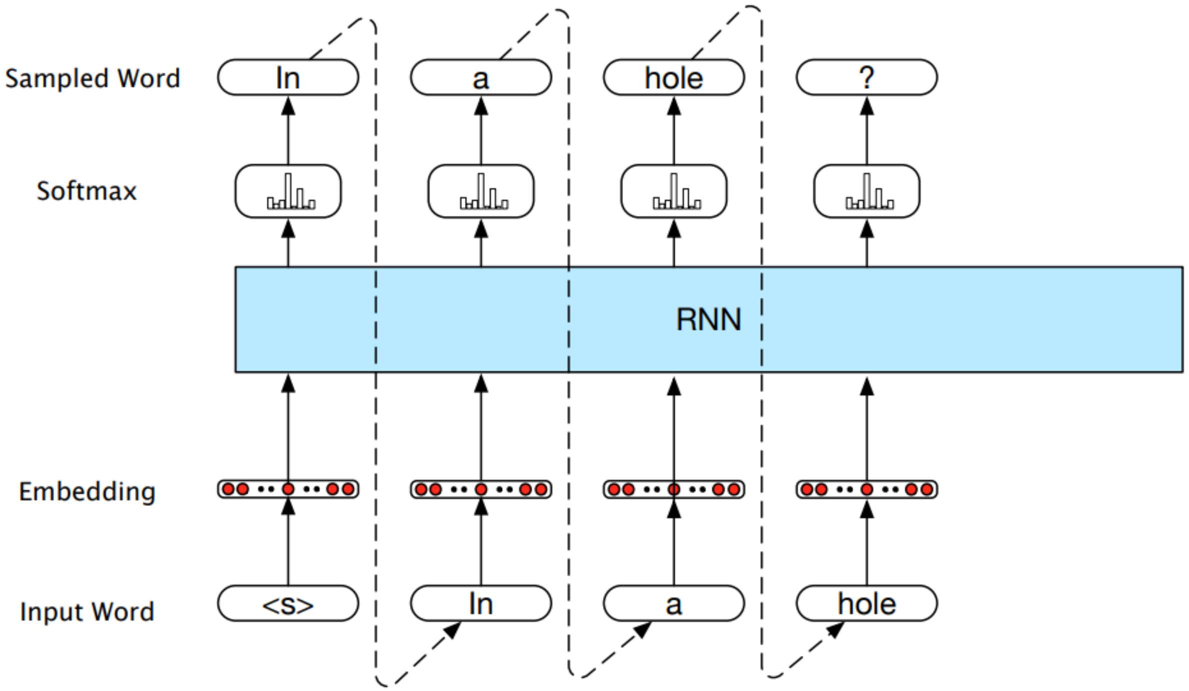
- E.g. Using a Twitter word embedding model on Reddit data
- E.g. Training sentiment detection on movie reviews but testing on product reviews
  - "Kangaroo"

How does this apply to text generation?

Problem with teacher forcing

Exposure bias: We're **training** the model to predict the next word, **given the previous true words**

But when we **generate** text, the model is looking at words **it generated**



Solutions

Minimum risk training:
(Shen et al. 2016, https://www.aclweb.org/anthology/P16-1159.pdf)
— define a loss function (e.g. negative BLEU) to compare
generated sequences against gold sequences
—Minimize risk (expected loss on training data) such that candidates
outputs with a smaller loss (higher BLEU score) have higher probability.

Reinforcement learning-based approaches:
(Ranzato et al. 2016 https://arxiv.org/pdf/1511.06732.pdf)
— use BLEU as a reward (i.e. like MRT)
— perhaps pre-train model first with standard teacher forcing.

GAN-based approaches ("professor forcing")
(Goyal et al. 2016, http://papers.nips.cc/paper/6099-professor-forcing-anew-algorithm-for-training-recurrent-networks.pdf)
— combine standard RNN with an adversarial model that aims to
distinguish original from generated sequences

Concluding thoughts

RNNs for language modeling

Generating text

- Greedy decoding
- Random sampling
- Beam search decoding

Training RNNs

- Teacher forcing
    - Exposure bias
- Alternatives
    - Minimum risk, reinforcement learning, GANs

Prompt engineering

Basic idea: Once a language model gets good enough, it can reliably respond to input text the way that a human would

- Because it has gotten **so** good at next-word-prediction

Prompt engineering: Methods for creating inputs to language models that **prompt** them to produce the right output

Few-shot learning: GPT-3 paper showed that if you show a few examples of what you want an LLM to do in the input prompt, it gets much better at doing them.

Lots more things people have come up with in the last couple of years!

- Hence the final assignment