CSCI 5541: Natural Language Processing

Lecture 7: Language Models: RNN, LSTM, and Seq2Seq

Dongyeop Kang (DK), University of Minnesota

dongyeop@umn.edu | twitter.com/dongyeopkang | dykang.github.io

computer science & engineering

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Announcement (0926)

- Continue lectures on neural LM and RNN LMs
- HW3 out
- Project description
- Project brainstorming due (Oct 1)

41 Grade HW2: Finetuning text classifier using HuggingFace

10 points • Sep 24 at 11:59pm

Ngram LM

Recap

Uni-gram

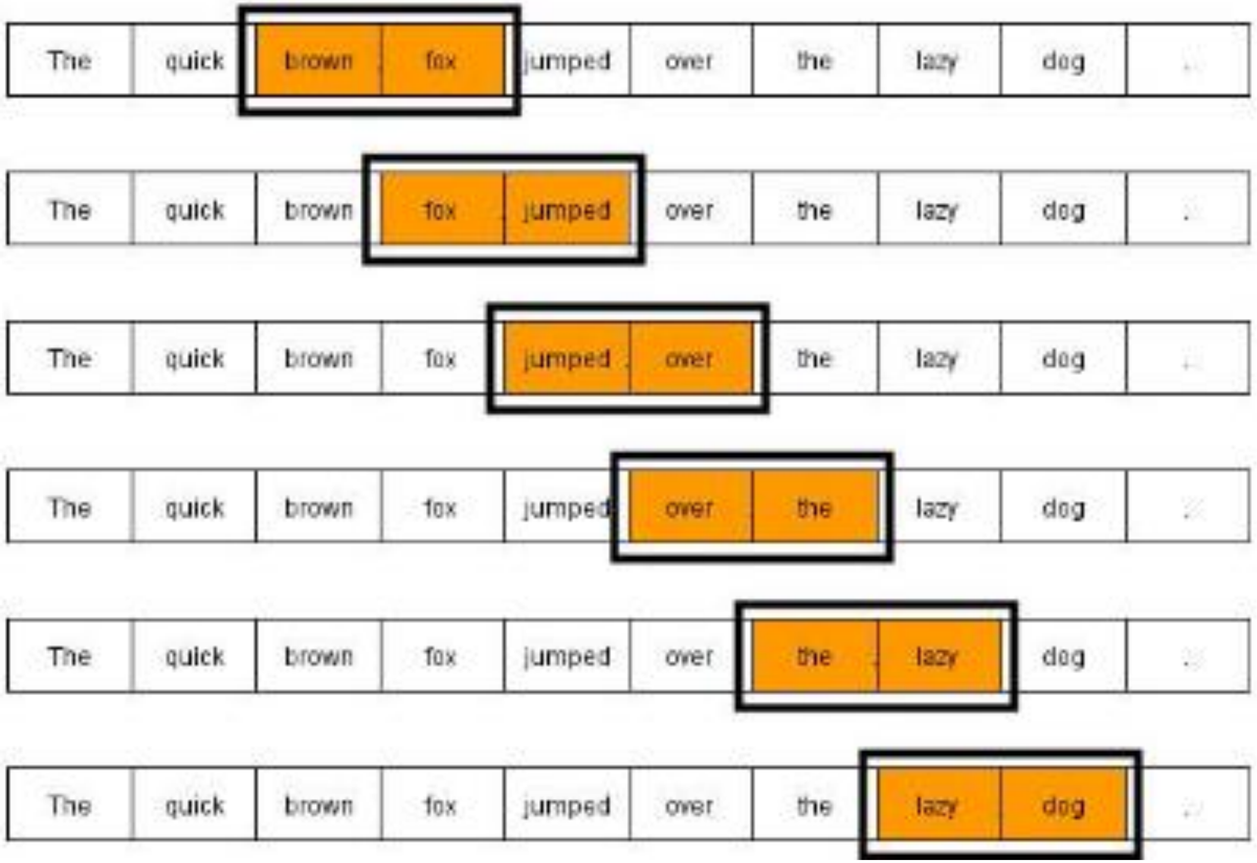
$$\prod_{i=1}^{n} P(w_i) \times P(STOP)$$

$$\frac{c(w_i)}{N}$$

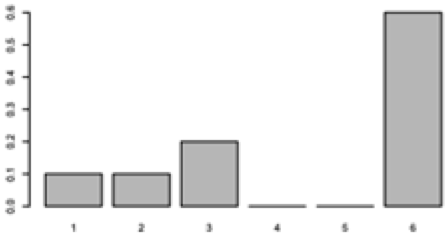
Bi-gram

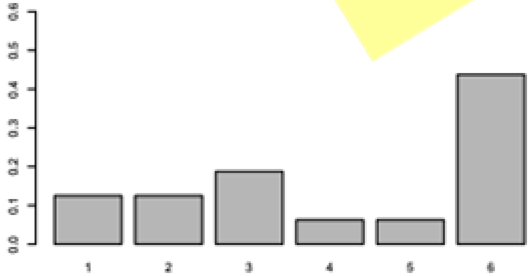
$$\prod_{i=1}^{n} P(w_i \mid w_{i-1}) \times P(STOP \mid w_n)$$

$$\frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$



Sparsity in Ngram LM





	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Figure 4.1 Bigram counts for eight of the words (out of $V = 1446$) in the Berkeley Restaurant Project corpus of 9332 sentences. Zero counts are in gray.

$$\frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \Rightarrow \frac{c(w_{i-1}, w_i) + \alpha}{c(w_{i-1}) + V\alpha}$$

$$\lambda p + (1 - \lambda) q$$

$$\begin{aligned} P(w_i \mid w_{i-2}, w_{i-1}) = {} & \lambda_1 P(w_i \mid w_{i-2}, w_{i-1}) \\ & + \lambda_2 P(w_i \mid w_{i-1}) \\ & + \lambda_3 P(w_i) \end{aligned}$$

Ngram LM vs Neural LM

To avoid the data sparsity problem from the ngram LM

Neural LM

Simple feed-forward multilayer perceptron
(e.g., one hidden layer)

$$x = [v(w_1); \ldots v(w_k)]$$

Concatenation (k x V)

w_1 = tried

w_2 = to

w_3 = prepare

w_4 = midterms

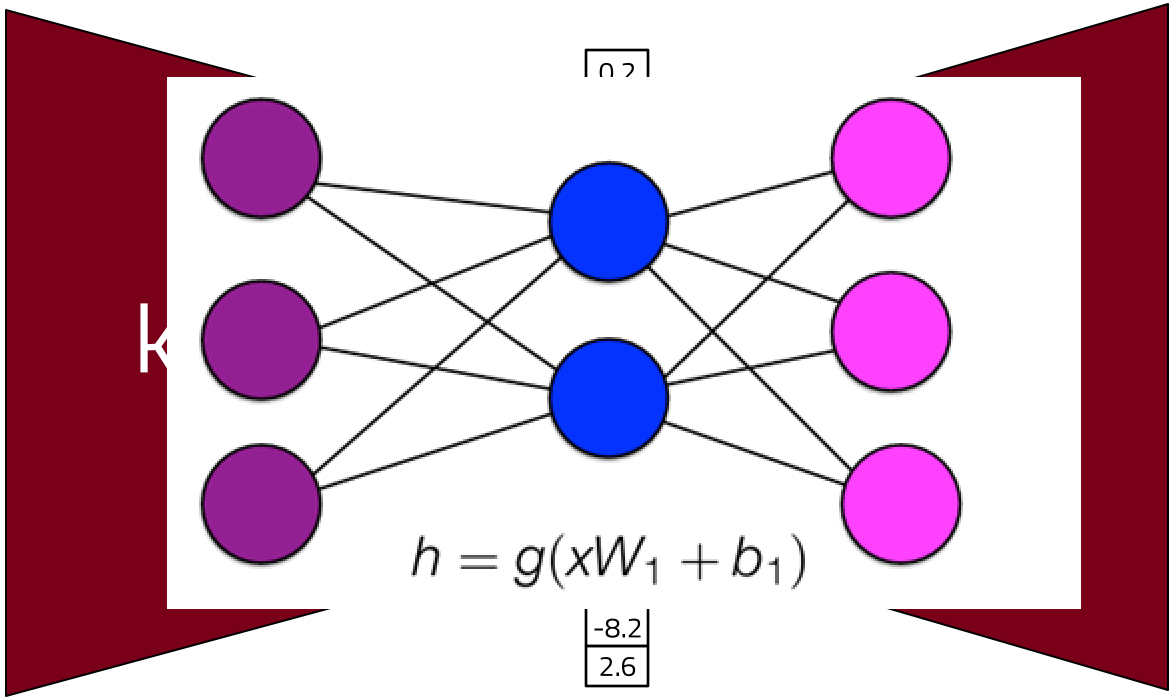
$v(w_1)$ = [1, 0, 0, 0]

$v(w_2)$ = [0, 1, 0, 0]

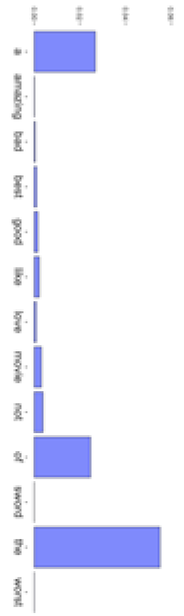
$v(w_3)$ = [0, 0, 1, 0]

$v(w_4)$ = [0, 0, 0, 1]

One-hot encoding



Distributed representation



Multi-class (Vocab) classification

Bengio et al. 2003, A Neural Probabilistic Language Model

Neural LM

$$P(w) = P(w_i | w_{i-k} .. w_{i-1}) = softmax\,(W \cdot \boldsymbol{h})$$

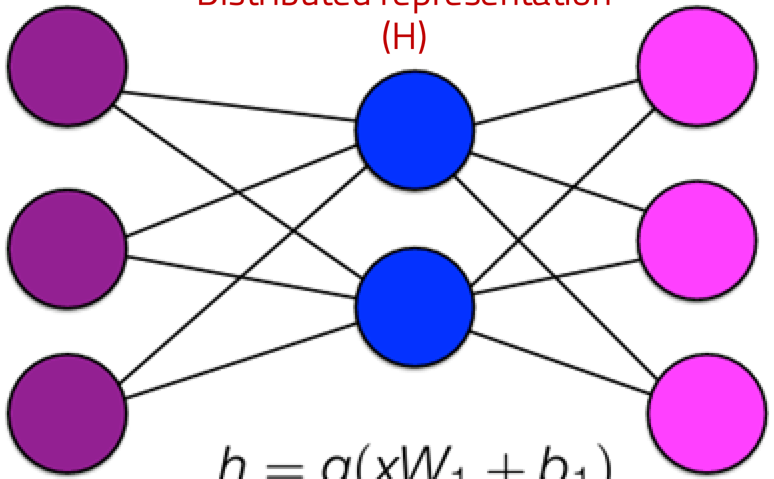
$W_1 \in \mathbb{R}^{kV \times H}$ $\quad$ $W_2 \in \mathbb{R}^{H \times V}$

$b_1 \in \mathbb{R}^{H}$ $\quad$ $b_2 \in \mathbb{R}^{V}$

One-hot encoding
(|x| = V)

Distributed representation
(H)

Output space: |y| = V



$$h = g(xW_1 + b_1)$$

$$x = [v(w_1); \ldots; v(w_k)]$$

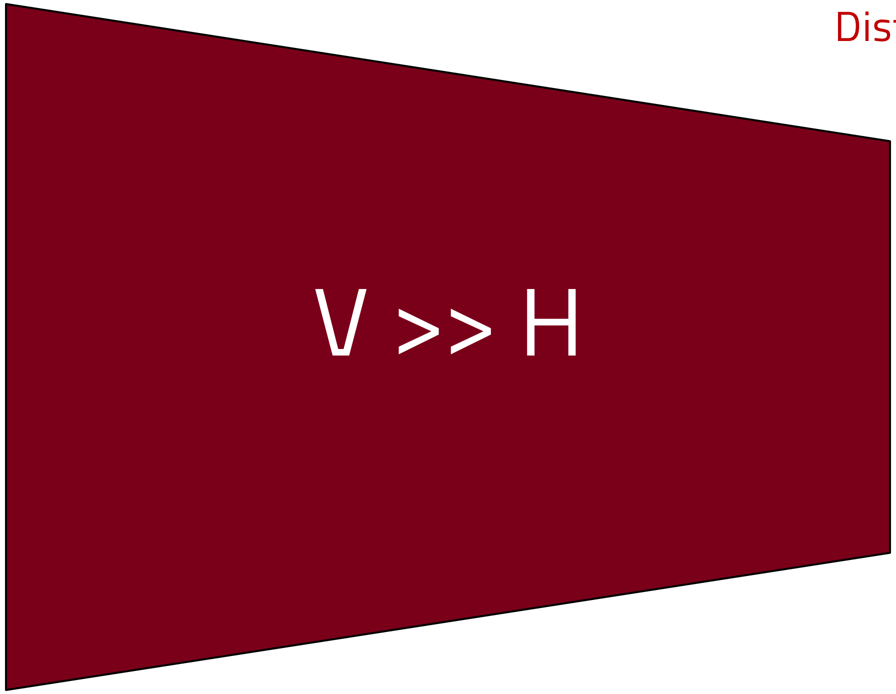
$$\hat{y} = \text{softmax}(hW_2 + b_2)$$

Bengio et al. 2003, A Neural Probabilistic Language Model

Neural LM

Represent high-dimensional words (and contexts) as low-dimensional vectors

One-hot encoding
(|x| = V)



Distributed representation
(|y| = H)

Bengio et al. 2003, A Neural Probabilistic Language Model

Conditioning context (X [k x V])

tried to prepare midterm but I was too tired of…

Next word to predict (Y)

Context window size: k=4

Conditioning context (X [k x V])

tried to prepare midterm but I was too tired of…

Next word to predict (Y)

Context window size: k=4

Conditioning context (X [k x V])

tried to prepare midterm but I was too tired of…

Next word to predict (Y)

Context window size: k=4

Neural LM against Ngram LM

Pros

- No sparsity problem
- Don't need to store all observed n-gram counts

Cons

- Fixed context window is too small (larger window, larger W)
  - Windows can never be large enough
- Different words are multiplied by completely different weights (W); no symmetry in how the inputs are processed.

Recap

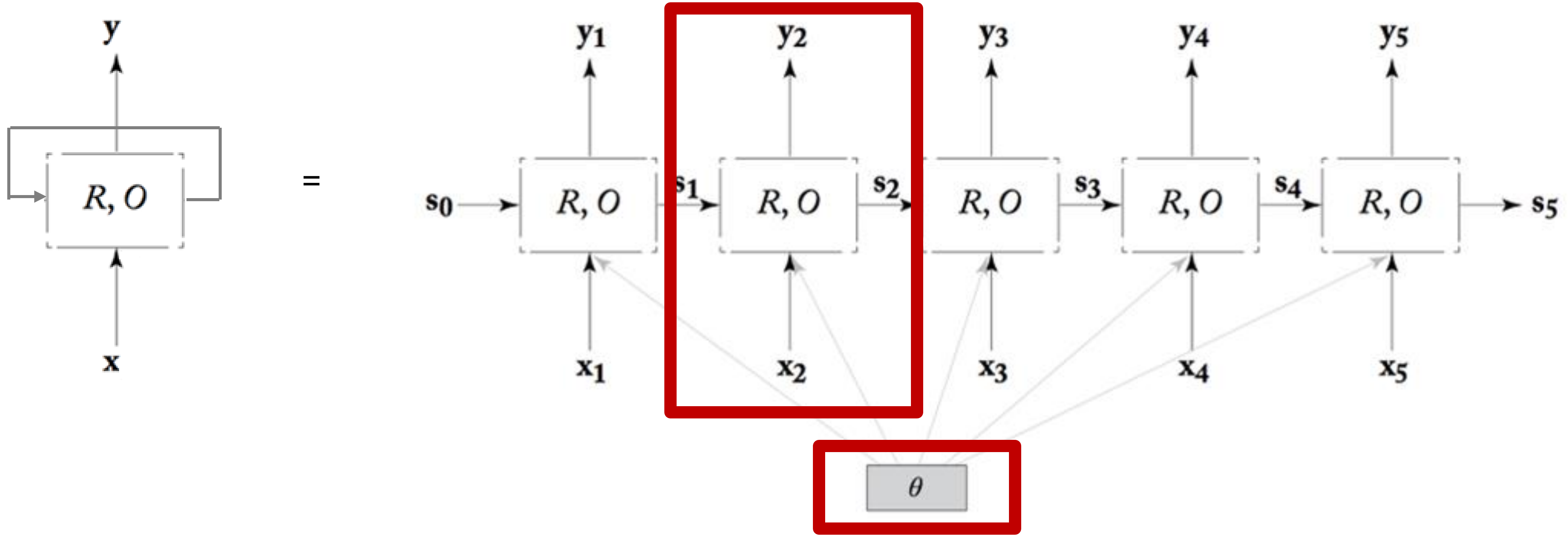
- ❑ Ngram LM → Neural LM : sparsity
- ❑ Neural LM → RNN LM : input size is not scalable
- ❑ RNN LM → LSTM LM:
- ❑ LSTM LM → Transformer LM:

Outline

- Recurrent Neural Network (RNN)
- Long Short-term Memory (LSTM)
- Implementation of RNN and LSTM using PyTorch
- Sequence-to-Sequence modeling
- Teaser: Transformer-based LMs
- Why language models are useful?

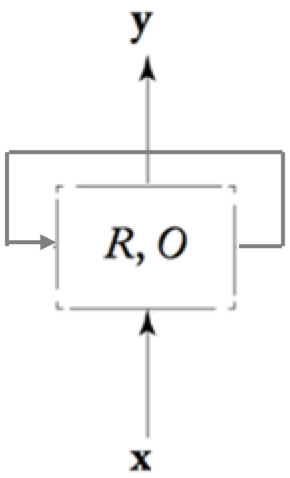
Recurrent Neural Network (RNN)

RNN allow arbitarily-sized conditioning contexts;
condition on the entire sequence history.



Goldberg 2017

Recurrent Neural Network



Neural-LM: $P(w) = P(w_i | w_{i-k} .. w_{i-1}) = softmax\,(W \cdot \boldsymbol{h})$

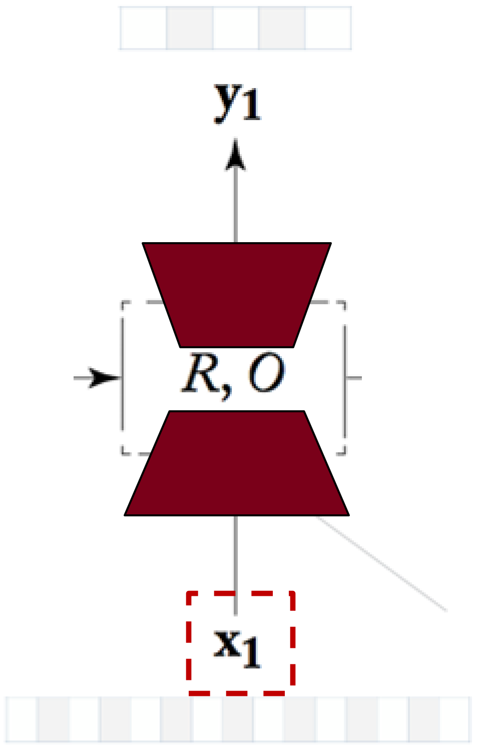
RNN: $P(w) = P(w_i | context)$
$= softmax\,(W \cdot \boldsymbol{h_i})$

Goldberg 2017

Recurrent Neural Network

- ❑ Each time set has two inputs:

- ❑ X_i (the observation at time step i):
  - ○ One-hot vector, feature vector, or distributed representation of input token at i step

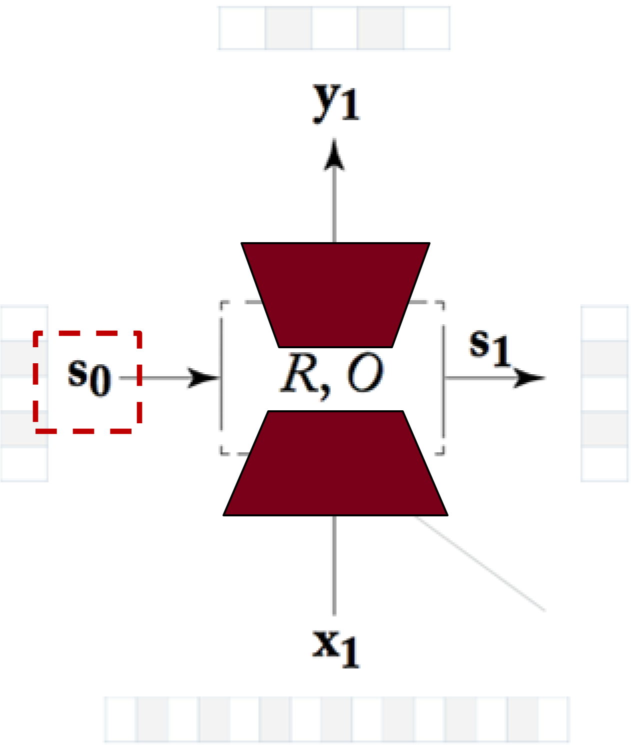


Recurrent Neural Network

- Each time set has two inputs:

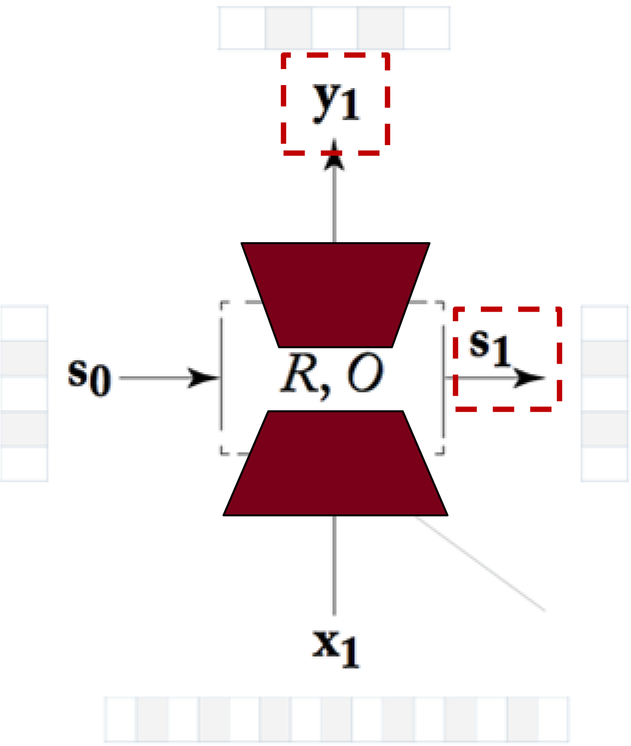
- X_i (the observation at time step i):
  - One-hot vector, feature vector, or distributed representation of input token at i step

- S_{i-1} (the output of the previous state):
  - Base case: $S_0 = 0$ vector



Recurrent Neural Network

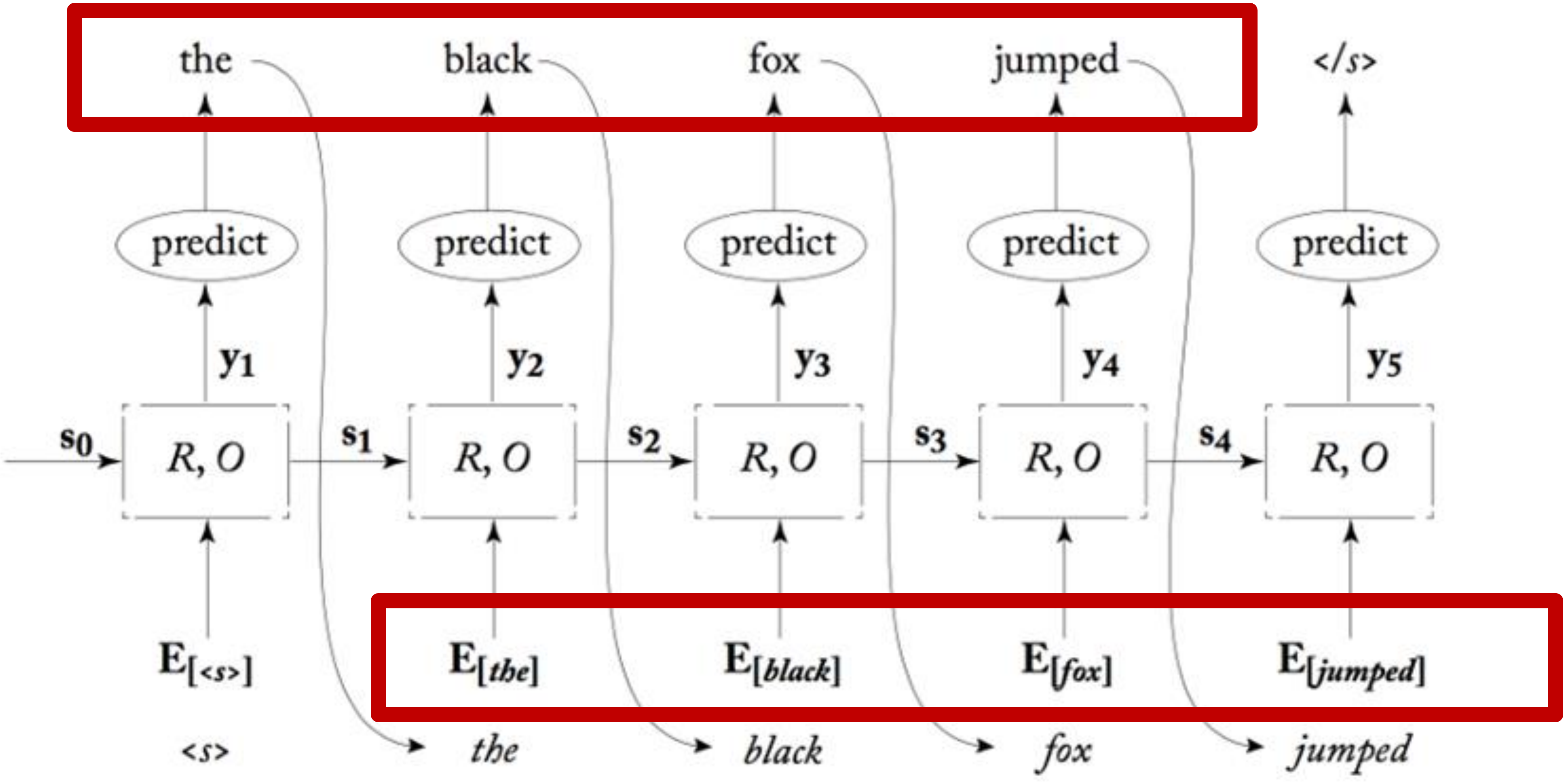
- Each time set has two outputs:
- $S_i = R\ (X_i, S_{i-1})$
  - R computes the output state as a function of the *current input* and *previous state*
- $y_i = O\ (S_i)$
  - O computes the output as a function of the *current output state*



RNN Training

output as shifted by one

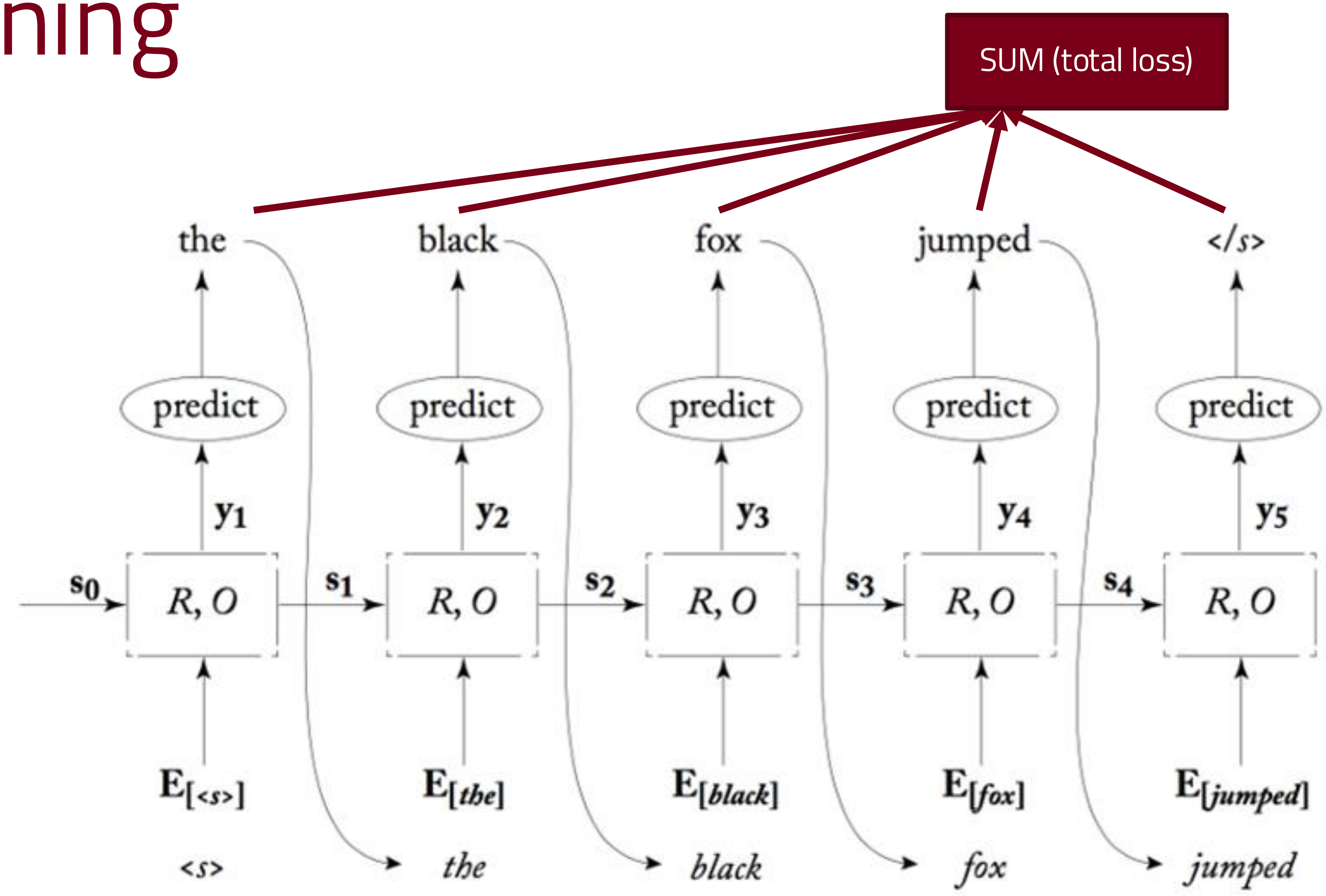
sequence of words



RNN Training

output as
shifted by one

sequence of
words

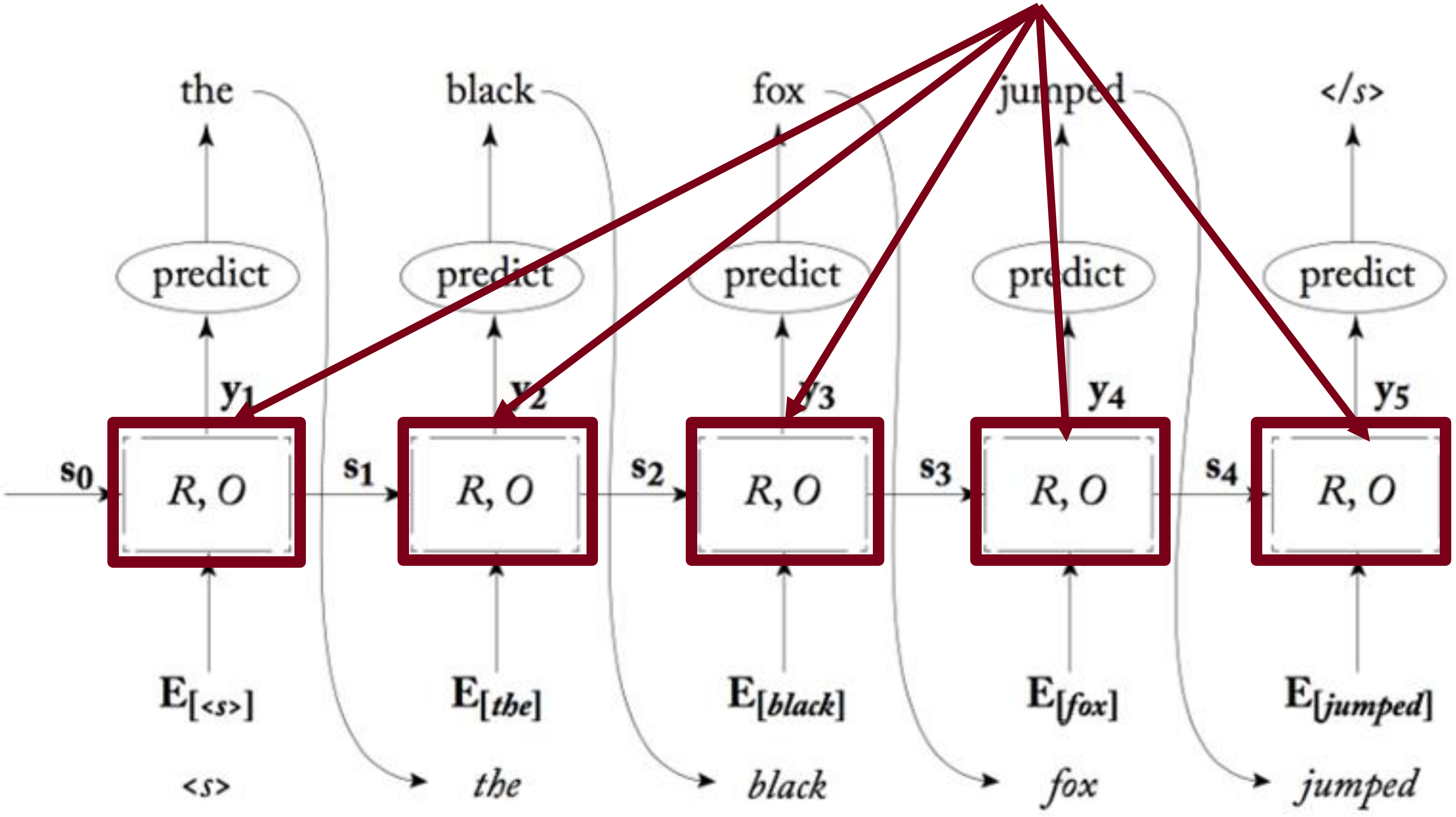


RNN Training

Parameters are shared!
Derivatives are accumulated.

output as
shifted by one

sequence of
words



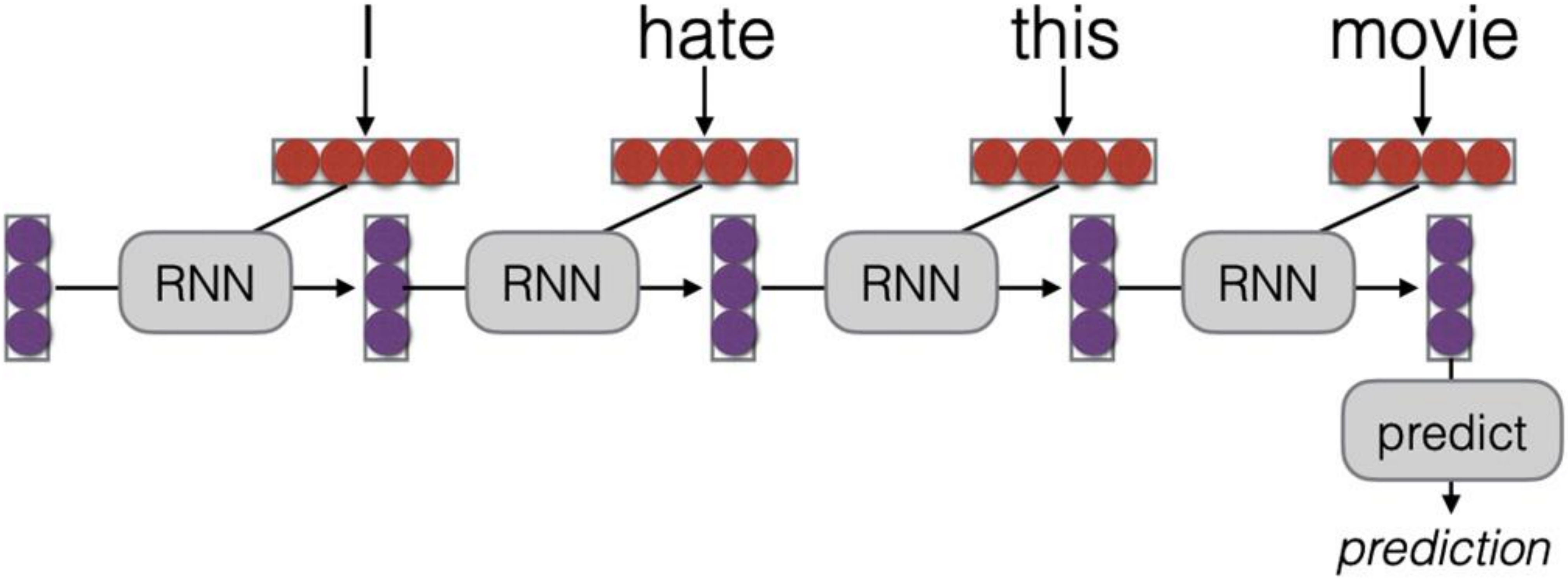
What can RNNs do?

- Represent a sentence
  - Read whole sentence, make a prediction

- Represent a context within a sentence
  - Read context up until that point

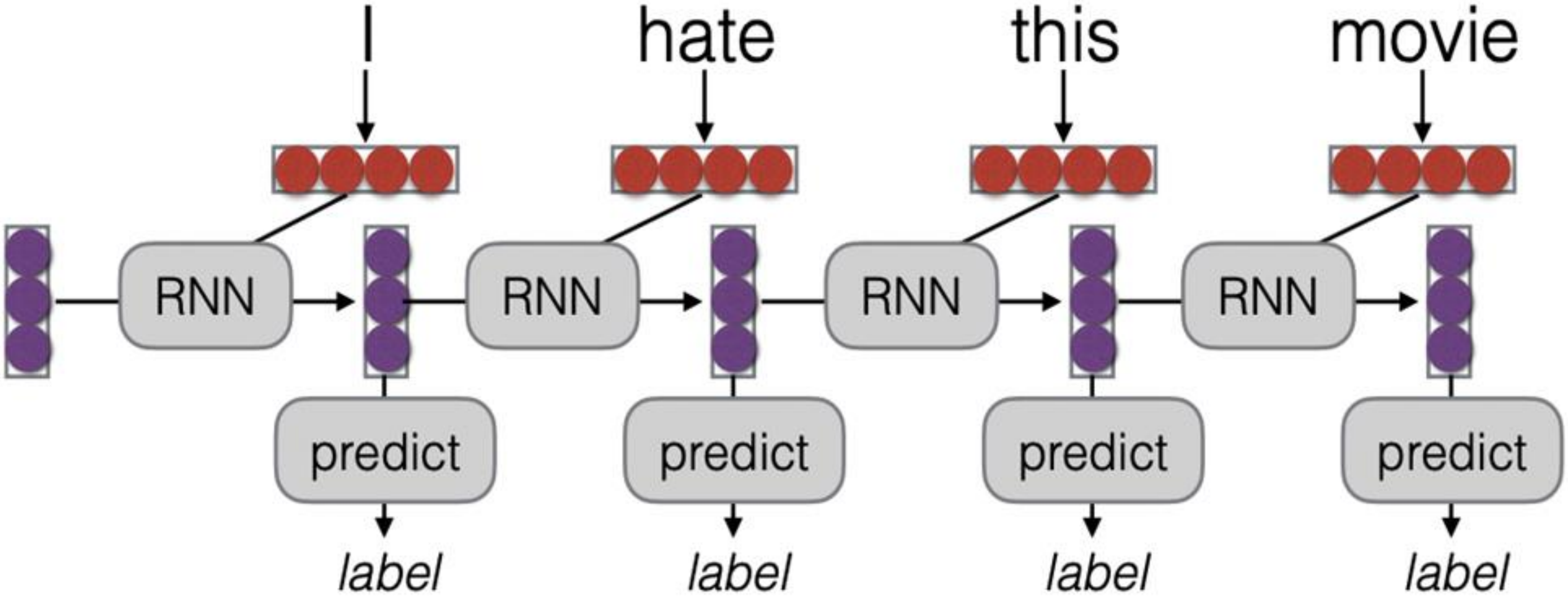
Representing Sentences

- ❑ Sentence classification
- ❑ Conditioned generation



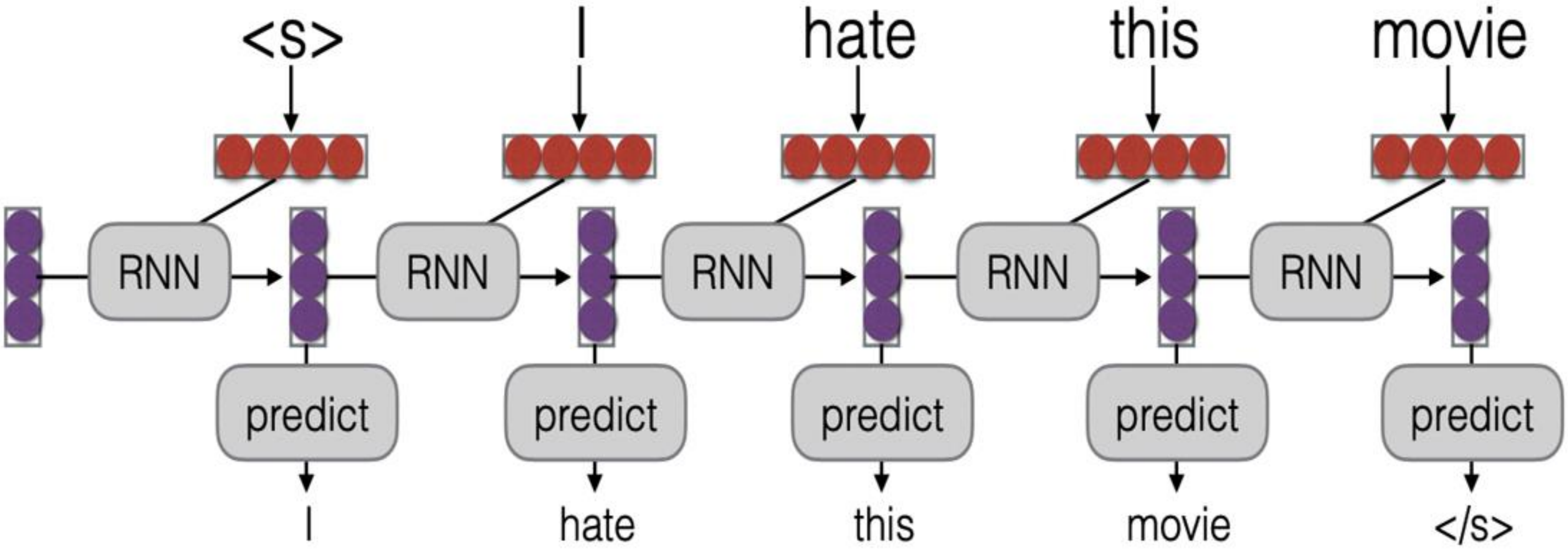
Representing Context within Sentence

- ❑ Tagging
- ❑ Language modeling

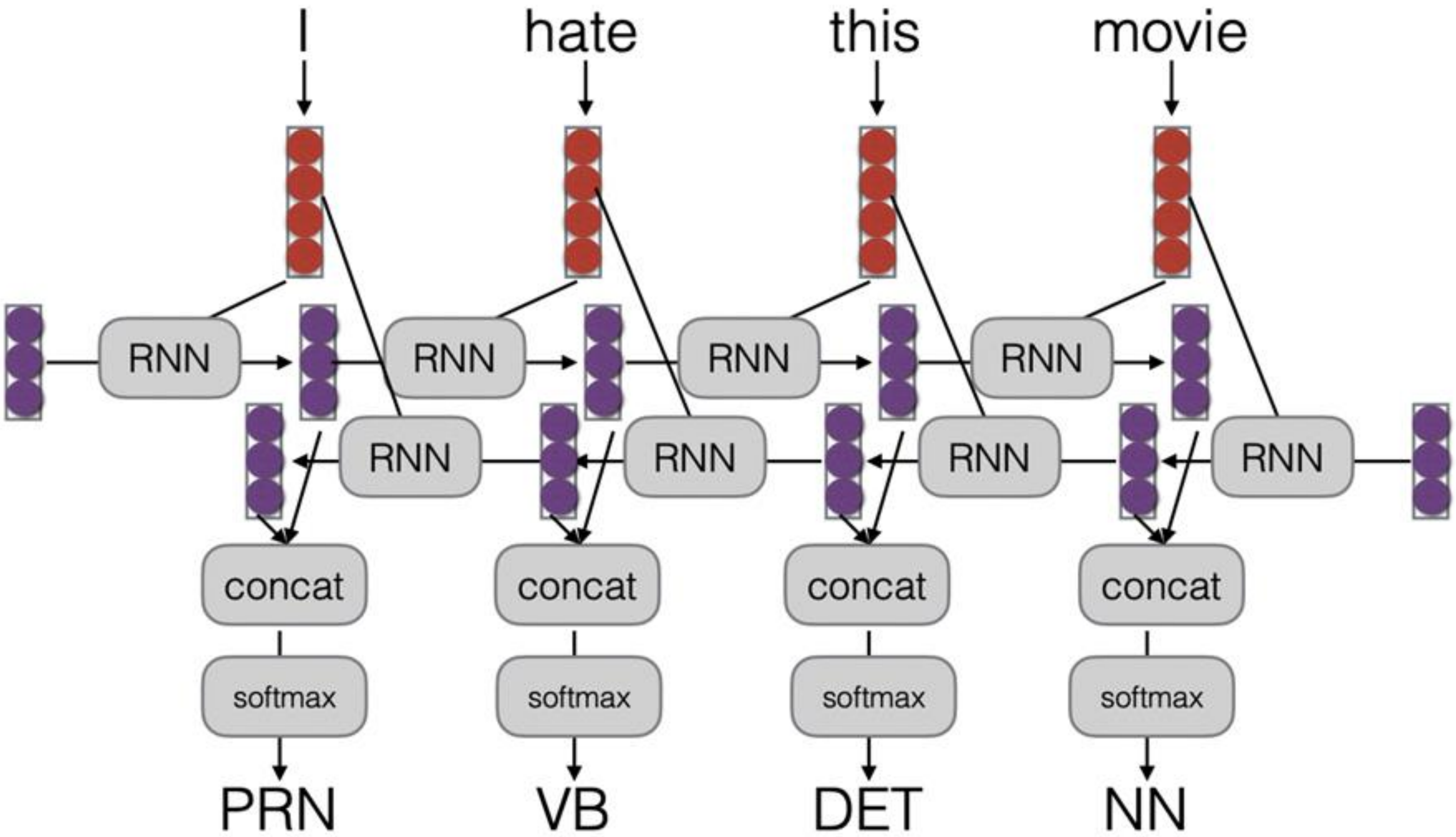


e.g., Language Modeling

- Language modeling is like a tagging task, where each tag is the next word!

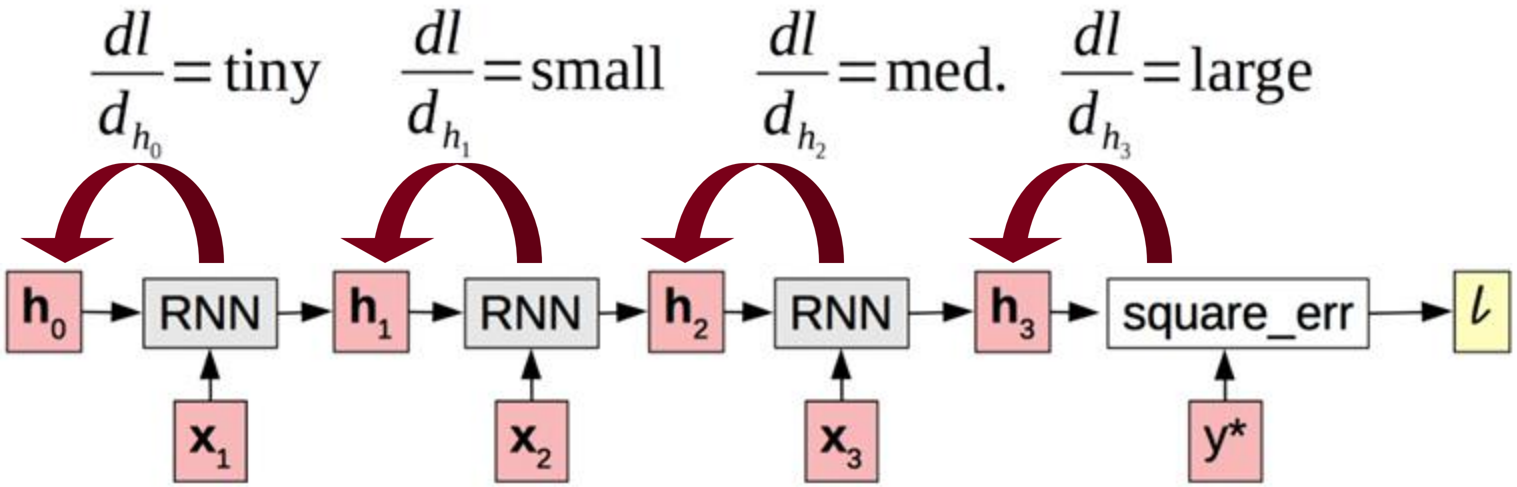


e.g., POS Tagging with Bi-RNNs



Vanishing Gradient

- Gradients decrease as they get pushed back



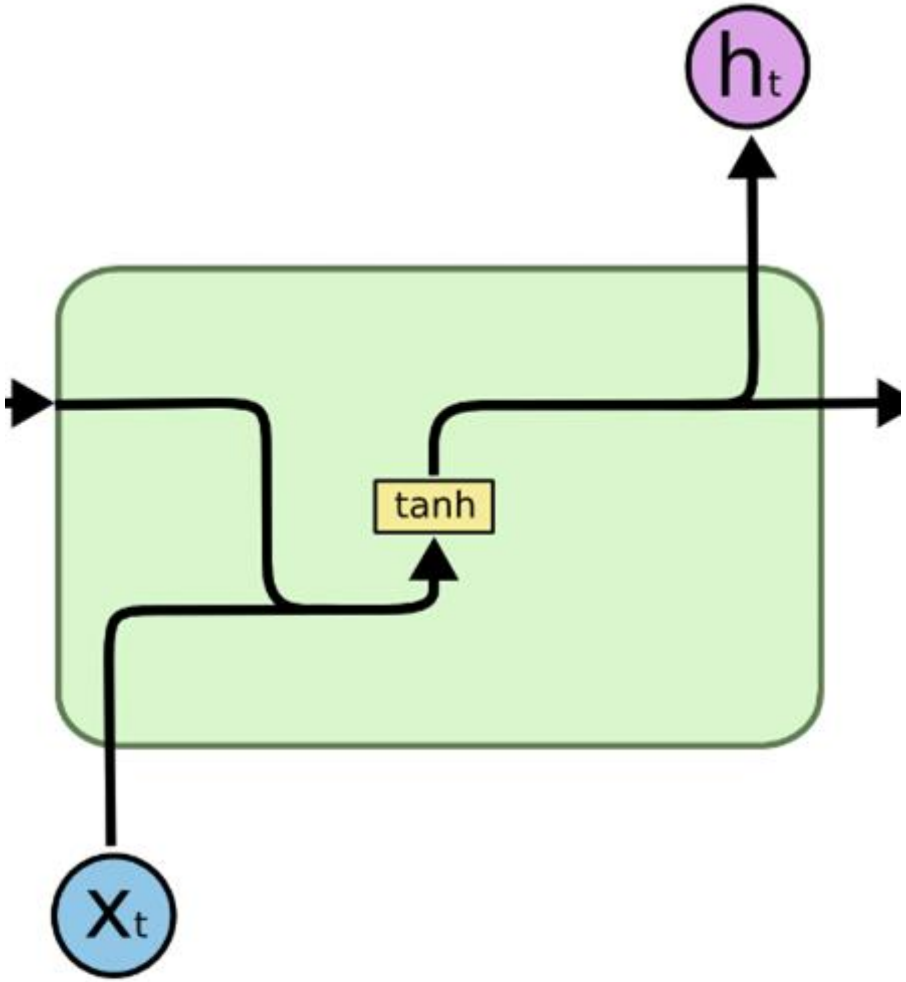
- Why? "Squashed" by non-linearities or small weights in matrices

A Solution: Long Short-term Memory (LSTM)

(Hochreiter and Schmidhuber 1997)

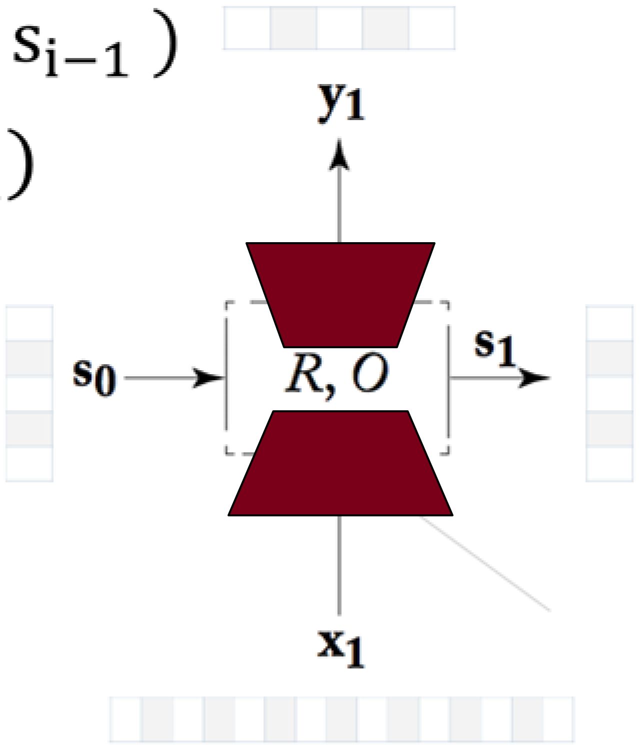
- Make **additive connections** between time steps
- Addition does not modify the gradient, no vanishing
- **Gates** to control the information flow

RNN Structure



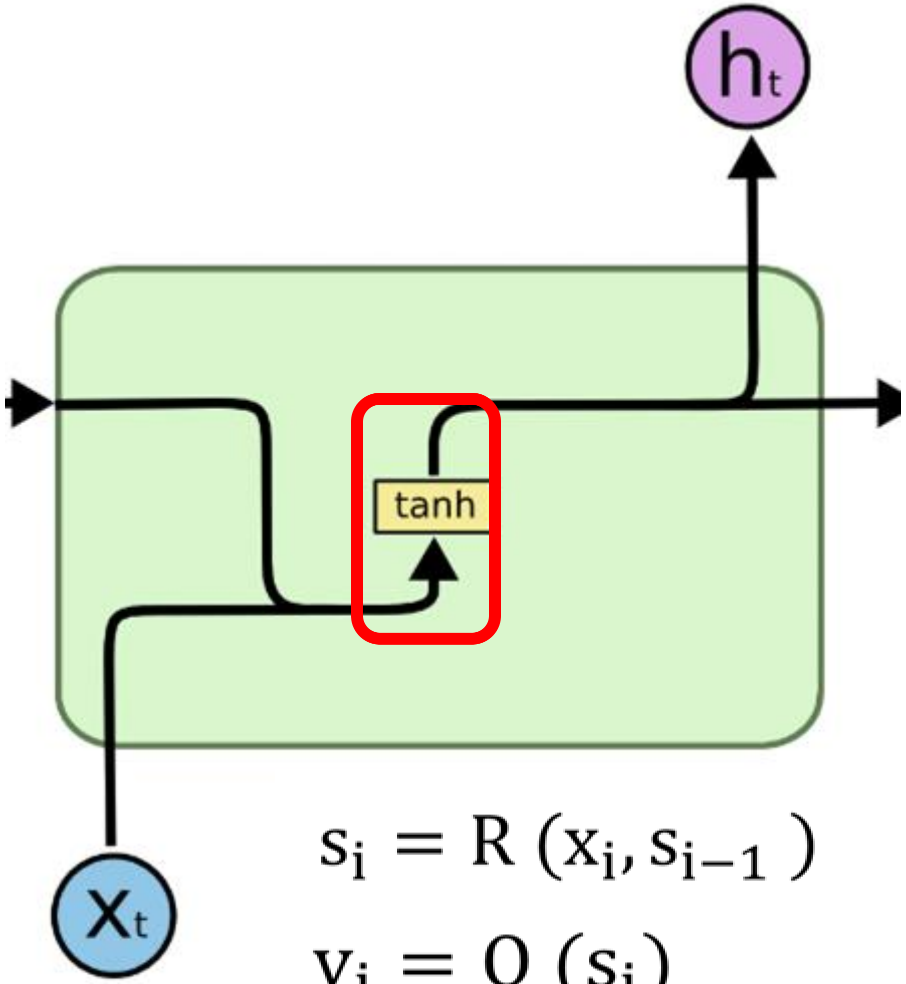
$$s_i = R(x_i, s_{i-1})$$

$$y_i = O(s_i)$$



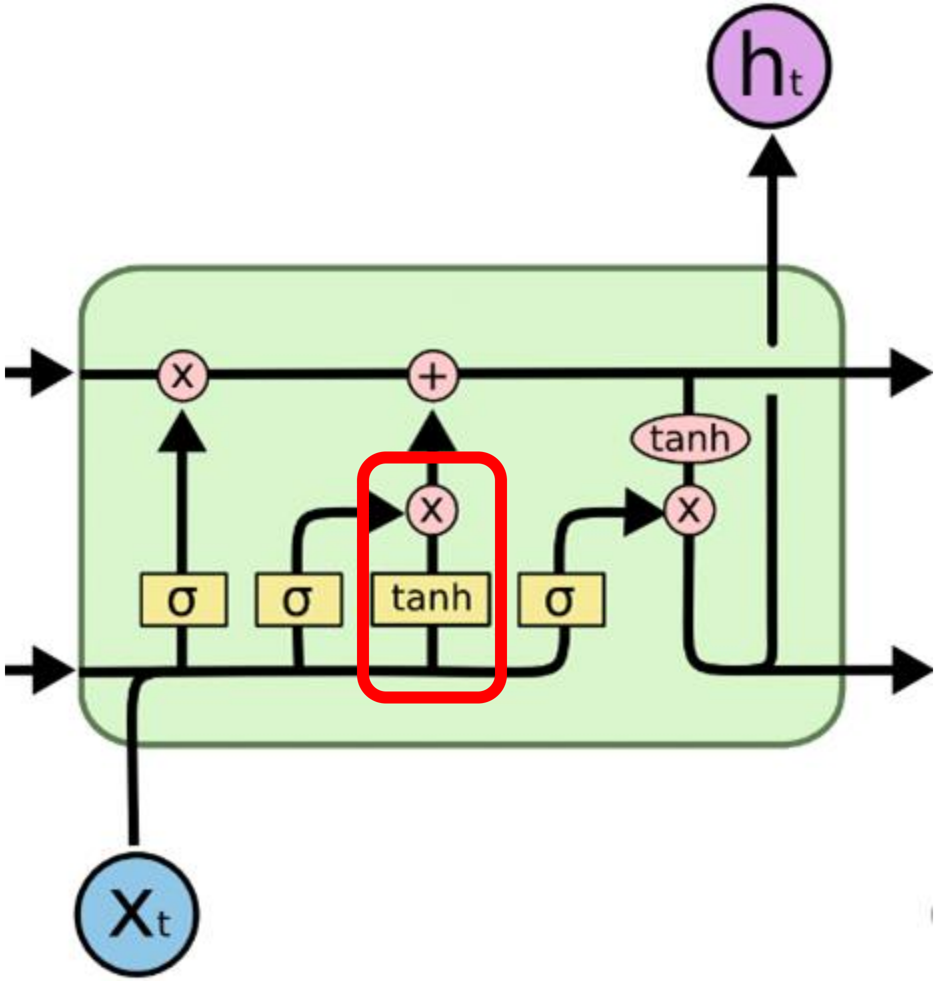
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN vs LSTM Structure



$$s_i = R\,(x_i, s_{i-1})$$

$$y_i = O\,(s_i)$$



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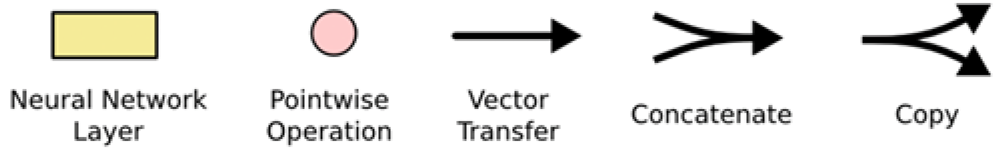
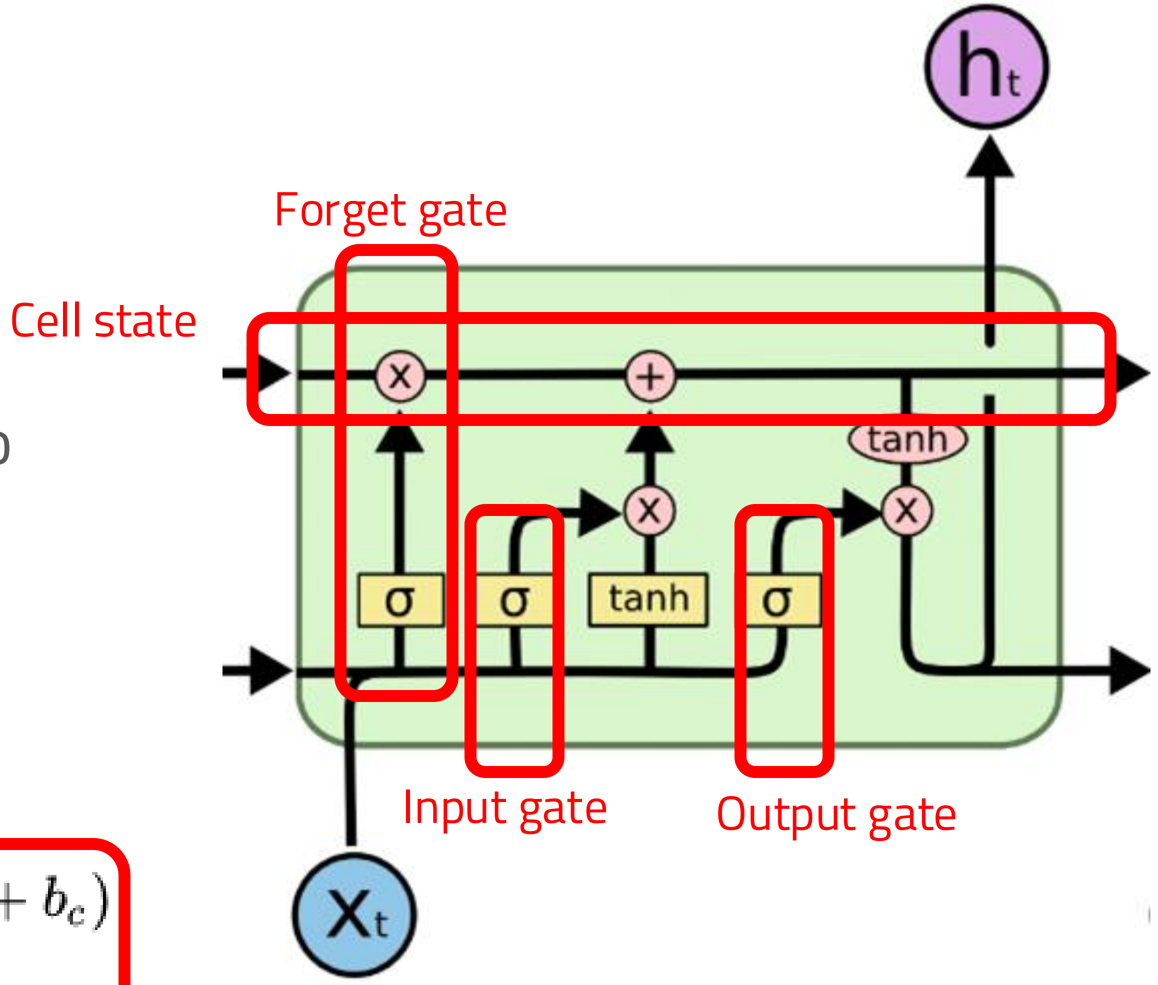
LSTM Structure



- **Forget gate:** what value do we try to add/forget to the memory cell?
- **Input gate**: how much of the update do we allow to go through?
- **Output gate**: how much of the cell do we reflect in the next state?

$$
\begin{aligned}
f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned}
$$



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM variant: Gated Recurrent Unit (GRU)

(Cho et al., 2014)

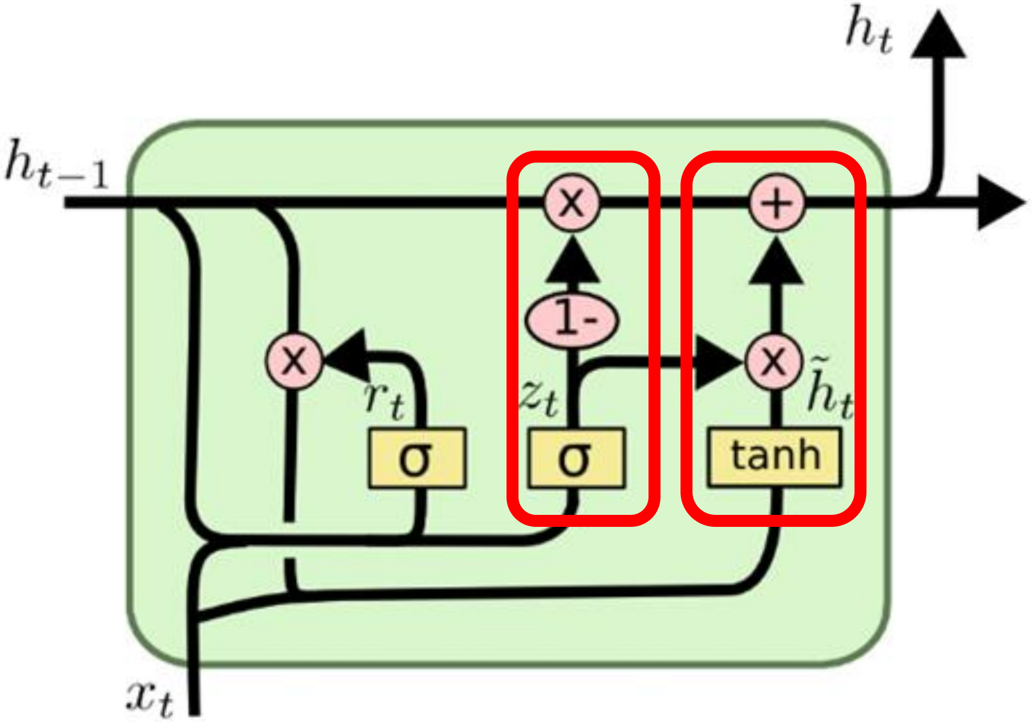
- Combines the forget and input gates into a single "update gate."
- Merges the cell state and hidden state
- And, other small changes

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$

$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$

$$h_t = \boxed{(1 - z_t)} \circ h_{t-1} + \boxed{z_t} \circ \sigma_h(W_h x_t + U_h(r_t \circ h_{t-1}) + b_h)$$

Additive or Non-linear



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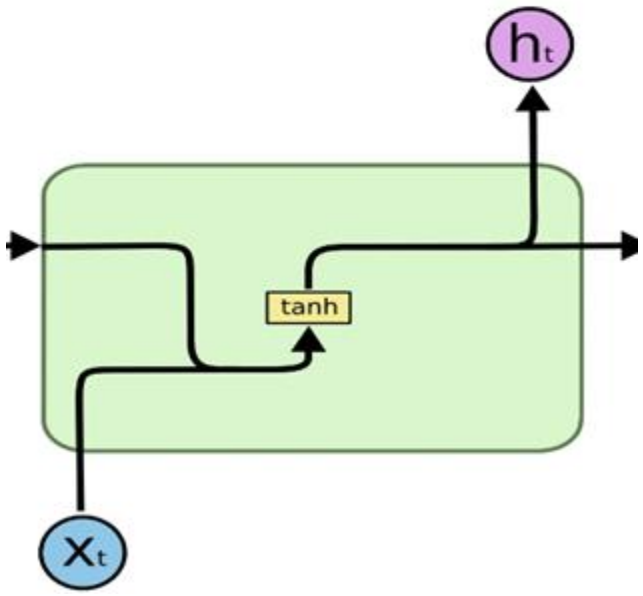
A Solution: Long Short-term Memory (LSTM)

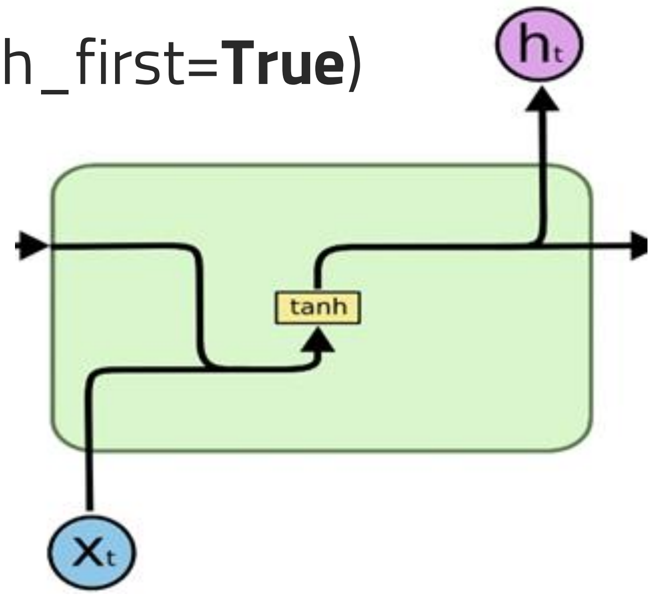
(Hochreiter and Schmidhuber 1997)

- Make **additive connections** between time steps
- Addition does not modify the gradient, no vanishing
- **Gates** to control the information flow

```python
class RNN(nn.Module):
    def __init__(self, input_size: int, hidden_size: int, output_size: int) -> None:
        super().__init__()
        ...
        self.i2h = nn.Linear(input_size, hidden_size, bias=False)
        self.h2h = nn.Linear(hidden_size, hidden_size)
        self.h2o = nn.Linear(hidden_size, output_size)

    def forward(self, x, hidden_state) :
        x = self.i2h(x)
        hidden_state = self.h2h(hidden_state)
        hidden_state = torch.tanh(x + hidden_state)
        out = self.h2o(hidden_state)
        return out, hidden_state
```

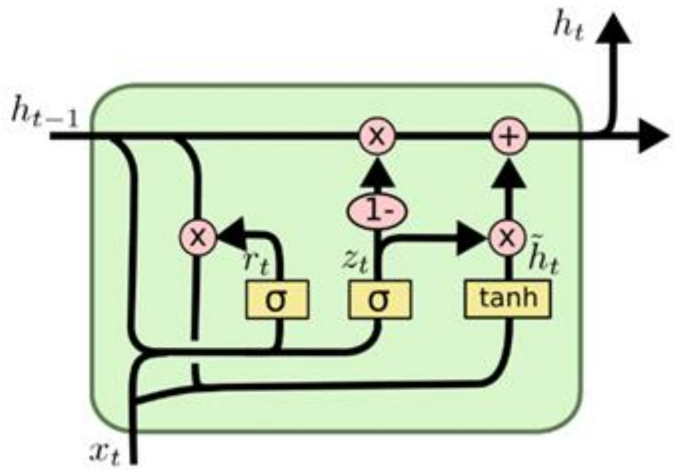


```
class RNN(nn.Module):
  def __init__(self, input_size, output_size, hidden_dim, n_layers):
        super(RNN, self).__init__()
        ...
        self.rnn = nn.RNN(input_size, hidden_dim, n_layers, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_size)

  def forward(self, x, hidden):
        r_out, hidden = self.rnn(x, hidden)
        r_out = r_out.view(-1, self.hidden_dim)

        return self.fc(r_out) , hidden
```



 # x (batch_size, seq_length, input_size)
 # hidden (n_layers, batch_size, hidden_dim)
 # r_out (batch_size, time_step, hidden_size)

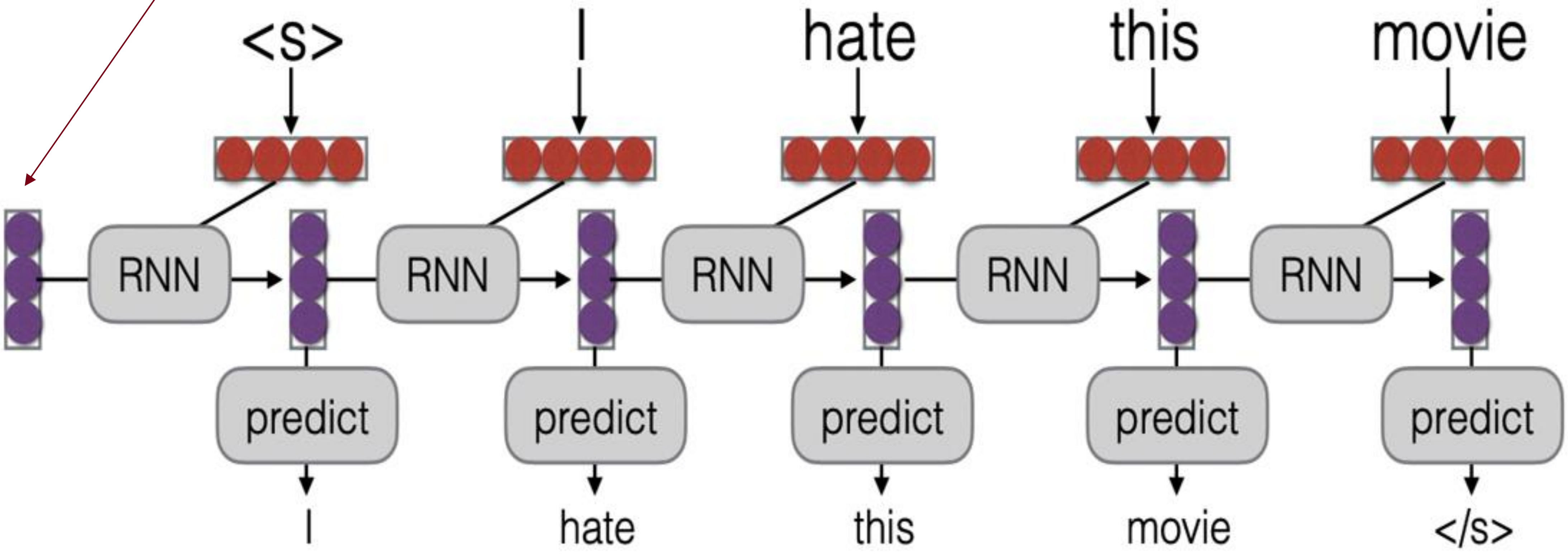
```
class LSTM (nn.Module):
   def __init__(self, num_classes, input_size, hidden_size, num_layers, 
seq_length):
      super(LSTM1, self).__init__()
      ...
      self.lstm = nn.LSTM(input_size=input_size, hidden_size=hidden_size, 
num_layers=num_layers, batch_first=True)
      self.fc =  nn.Linear(hidden_size, num_classes)
      self.relu = nn.ReLU()

   def forward(self,x):
      h_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size))
      c_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size))
      output, (hn, cn) = self.lstm(x, (h_0, c_0))
      hn = hn.view(-1, self.hidden_size)
      return self.fc (self.relu(hn))
```



Connecting RNN to RNN for sequence-to-sequence (seq2seq) modeling

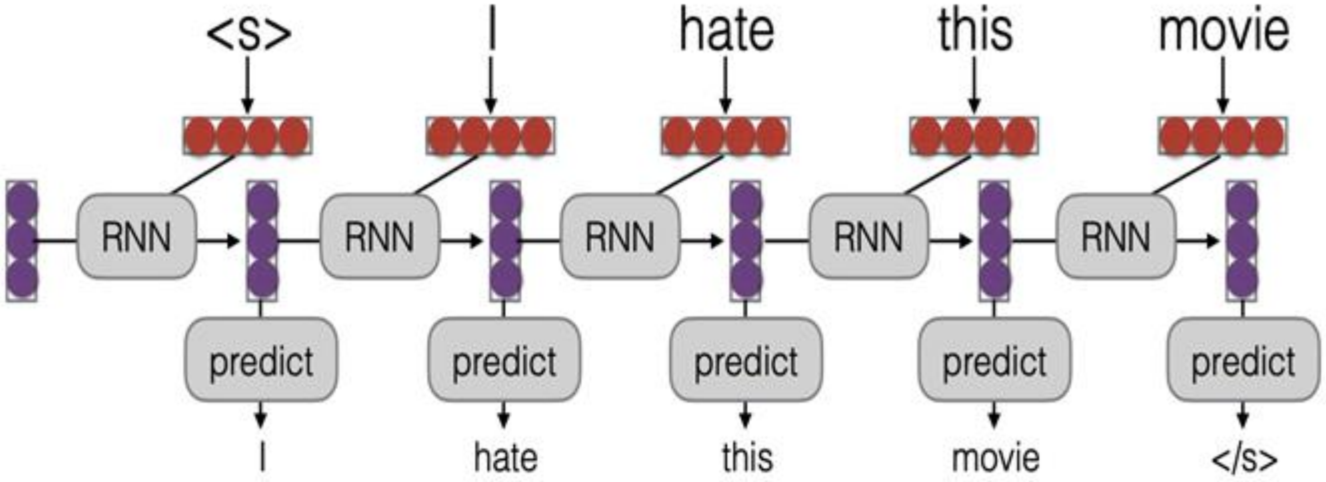
RNN (decoder) for language modeling

Randomly initialized hidden state h_t at time step $t = 0$



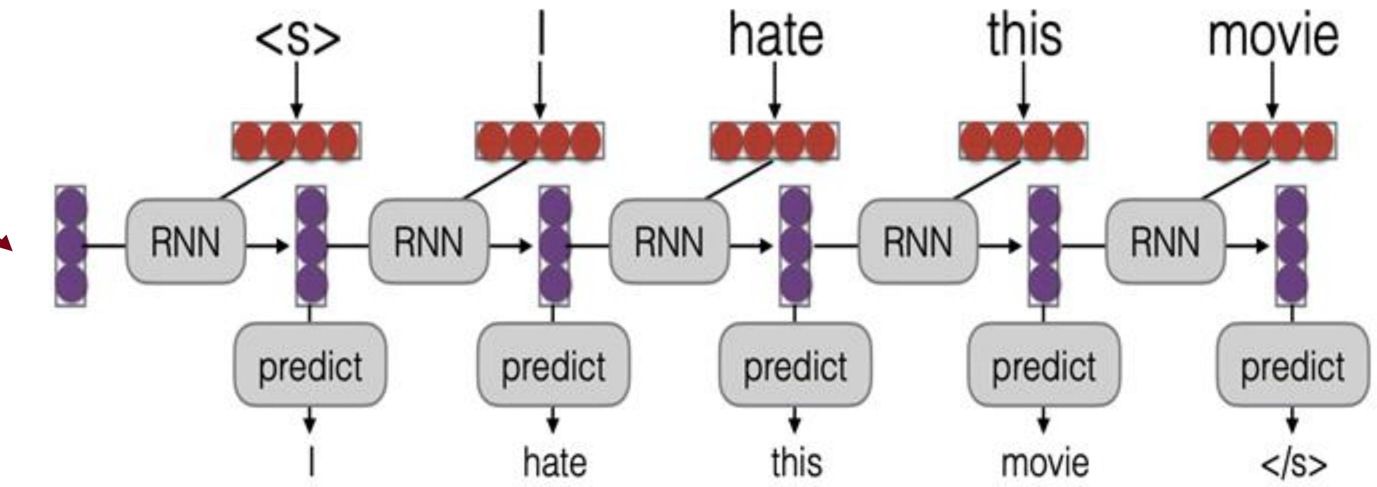
RNN (decoder) for language modeling

What if we encode some specific context, instead of random state?



RNN (encoder) - RNN (decoder) for machine translation

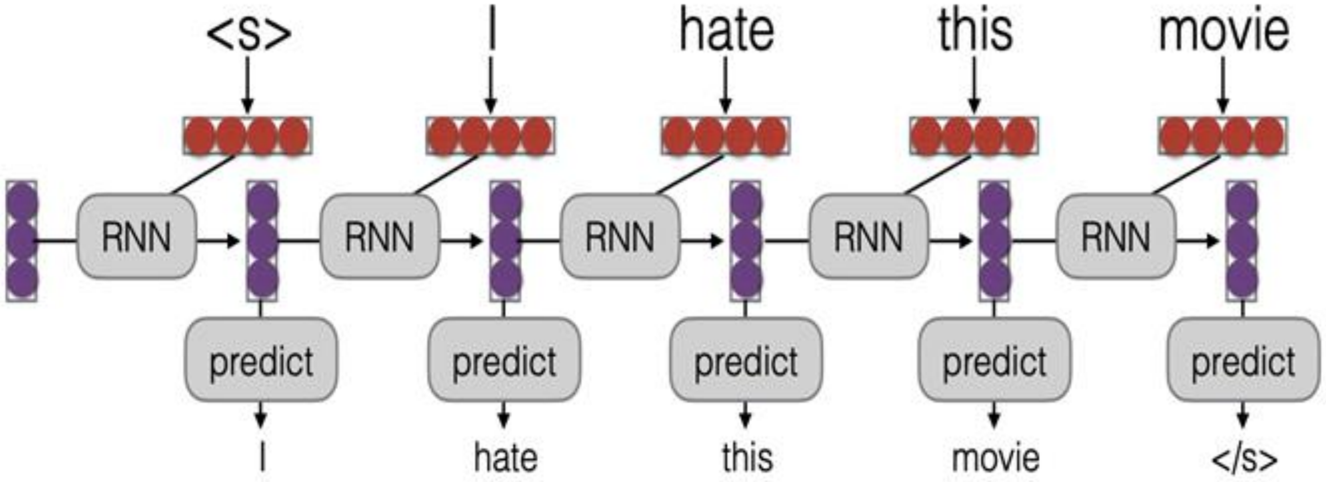
“나는 이 영화가 싫어요”
“Odio esta película”



RNN (encoder) - RNN (decoder) for dialogue generation

"나는 이 영화가 싫어요"
"Odio esta película"

"what do you think about *Avengers: Endgame*?"



RNN (encoder) - RNN (decoder) for question answering

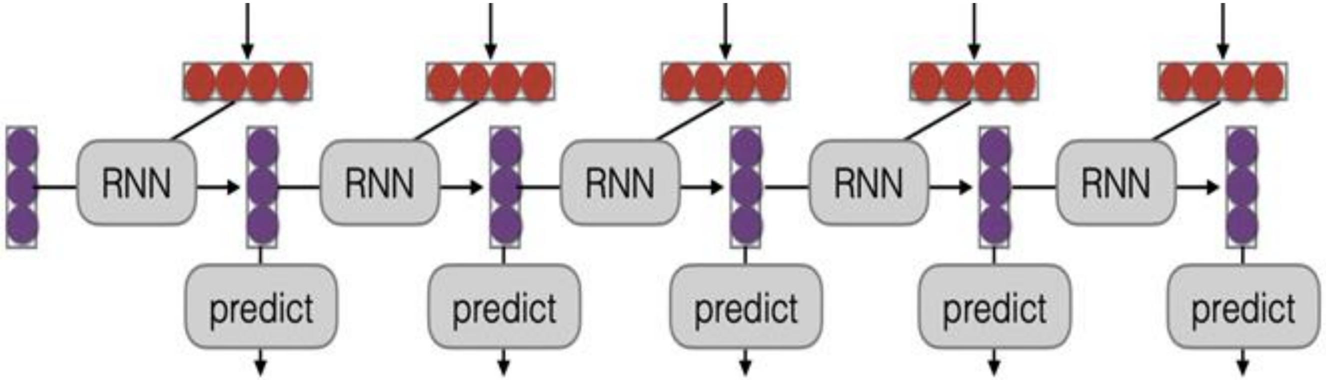
"나는 이 영화가 싫어요"
"Odio esta película"

"what do you think about *Avengers: Endgame*?

When is the film made?

<s>

This film is made in 1997

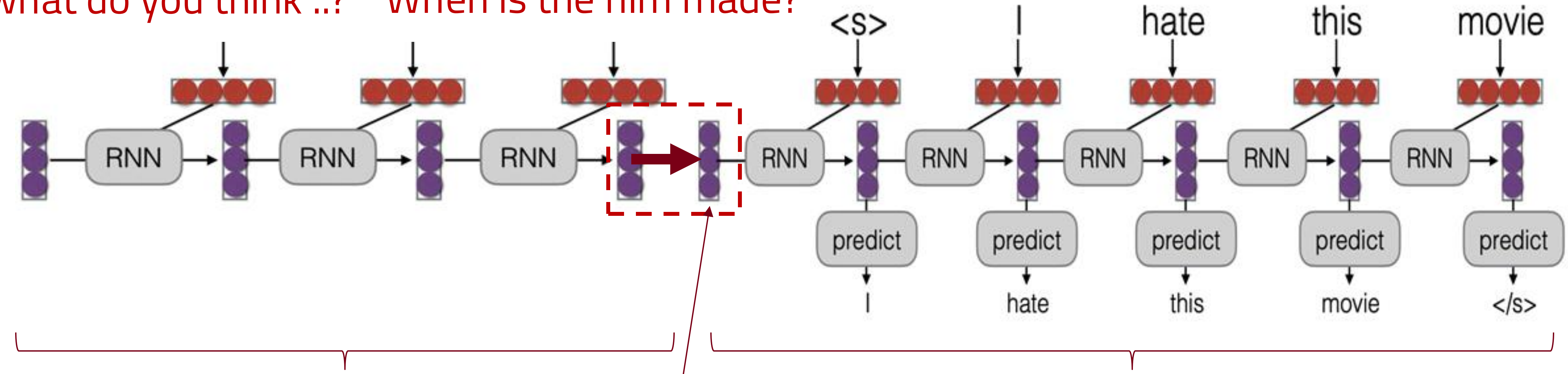


This film is made in 1997

Sequence-to-sequence modeling using RNN (encoder) - RNN (decoder)

"나는 이 영화가 싫어요"

"what do you think ..? When is the film made?

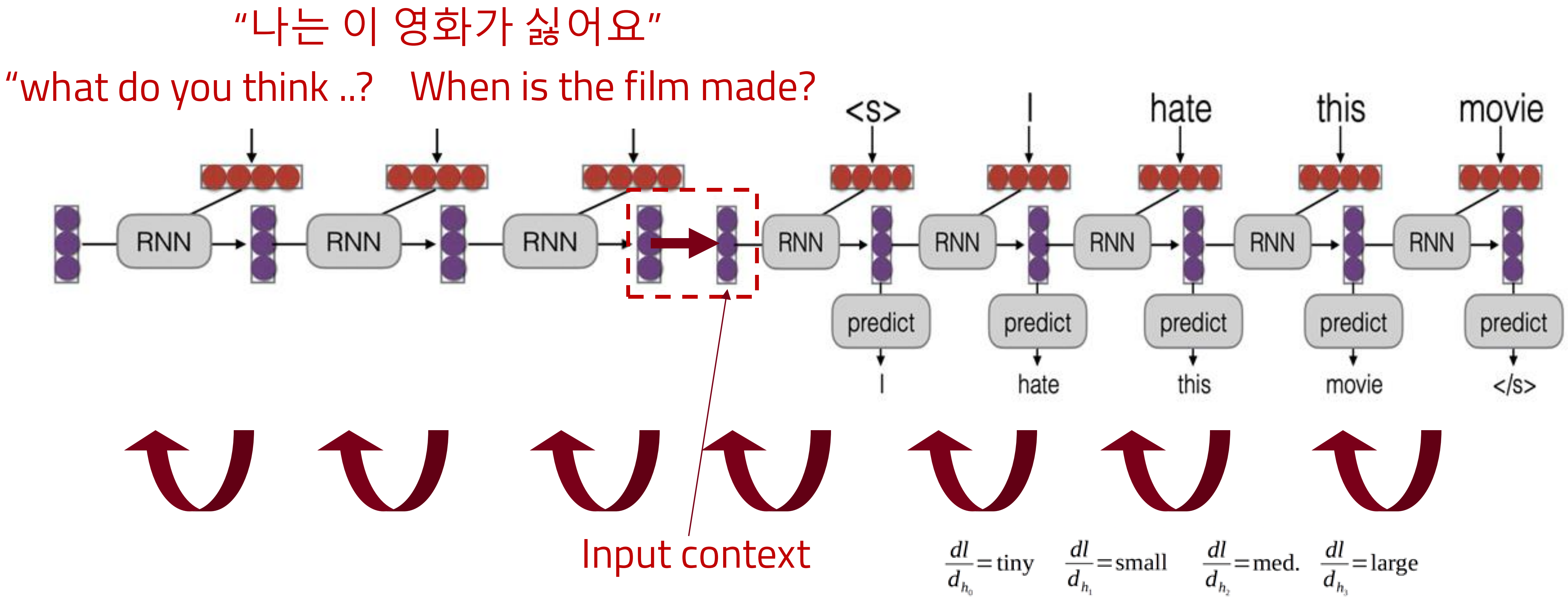


Encoder: encoding input sequence

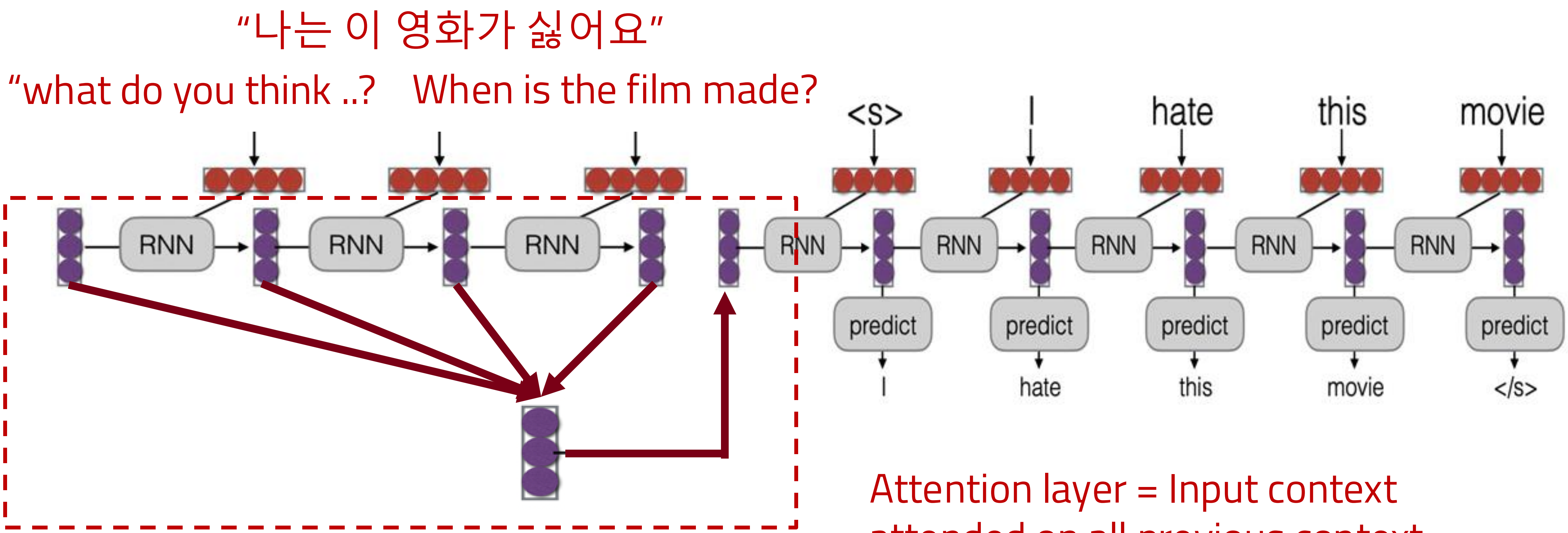
Input context

Decoder: decoding output sequence

Problem: forgetting input context as input gets longer



Solution (teaser): Seq2seq with attention



Attention layer = Input context attended on all previous context (will be covered more in Transformer)

Announcement (0215)

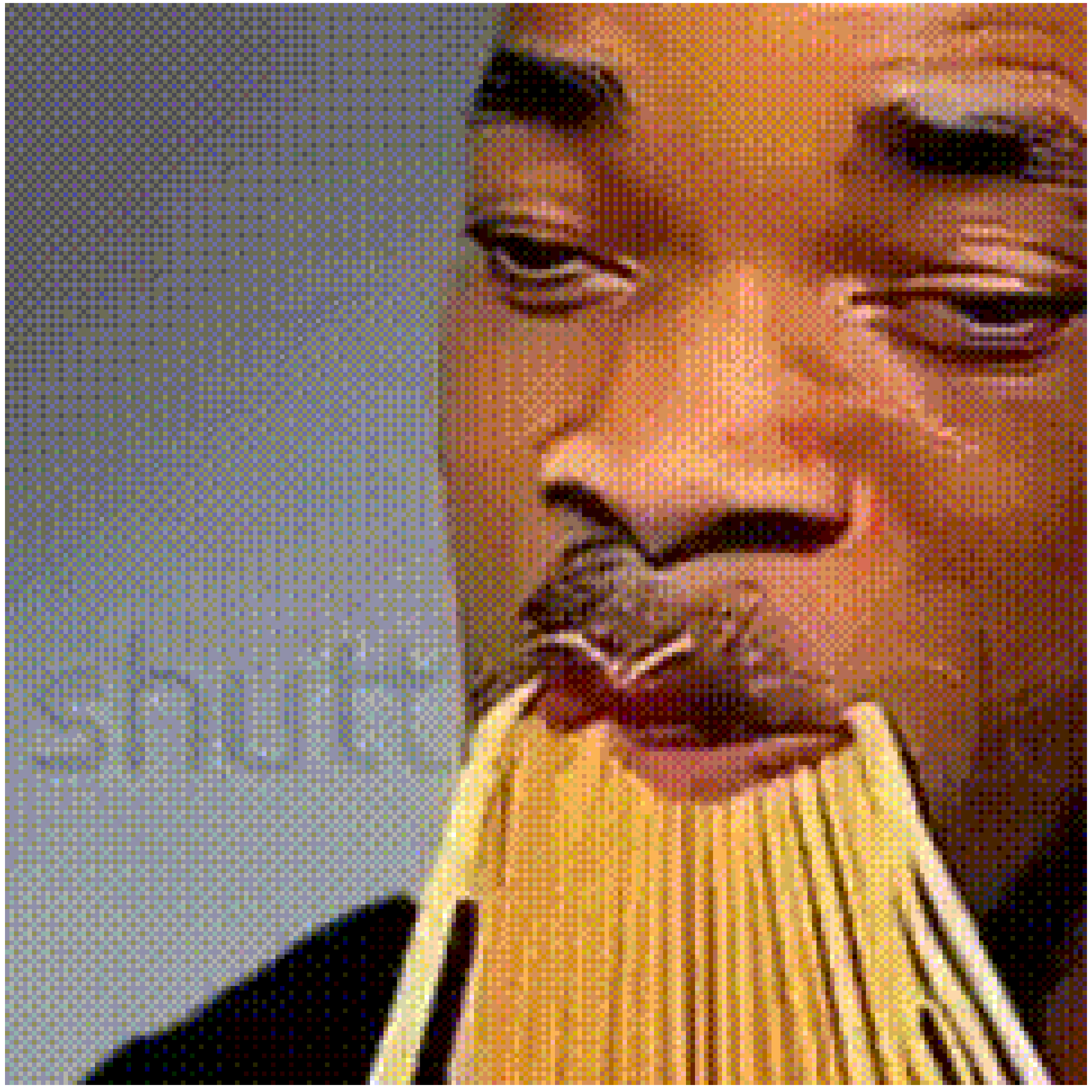
- Continue lecture on *Language Models (2): RNNs, LSTMs, and Seq2seq*
  - State-of-the-art Language Models
  - Why better language models are useful?
- Project Guideline
- Dues:
  - Team formation (Feb 16)
  - Reading assignment #1 (Feb 16)

Feb 13	Language Models (2): RNNs, LSTMs and Sequence-to-Sequence
Feb 15	Project Guideline Team formation due
Feb 20	No Class (AAAI)
Feb 22	Language Models (3): Search and Decoding HW2 due HW3 out

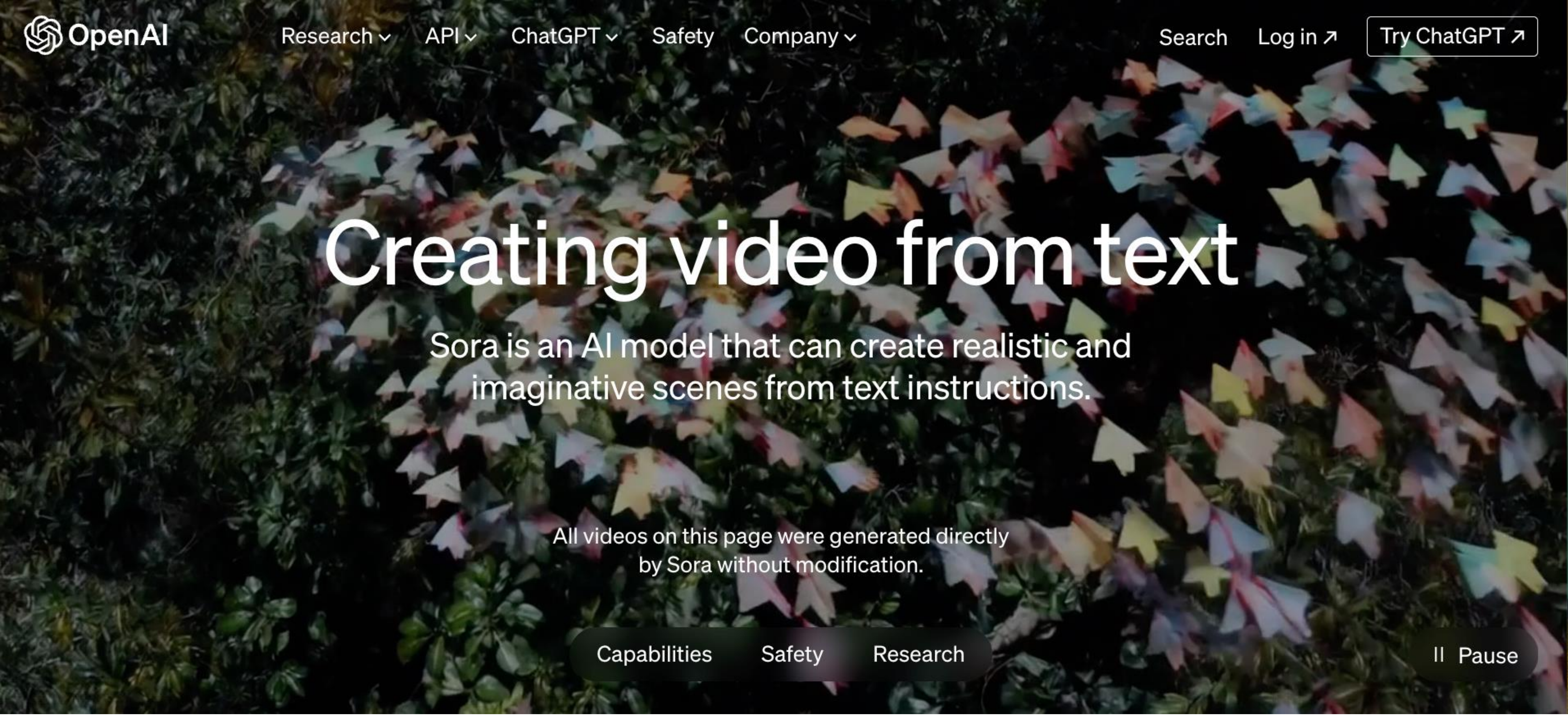
63 Grade HW1: Finetuning text classifier using HuggingFace
15 points • Feb 11 at 11:59pm

13 Grade Team formation
1 point • Feb 16 at 11:59pm

10 Grade Reading assignment #1
5 points • Feb 16 at 11:59pm



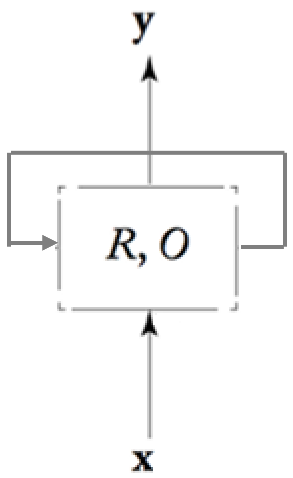
03 / 2023 https://www.reddit.com/r/StableDiffusion/comments/1244h2c/will_smith_eating_spaghetti/



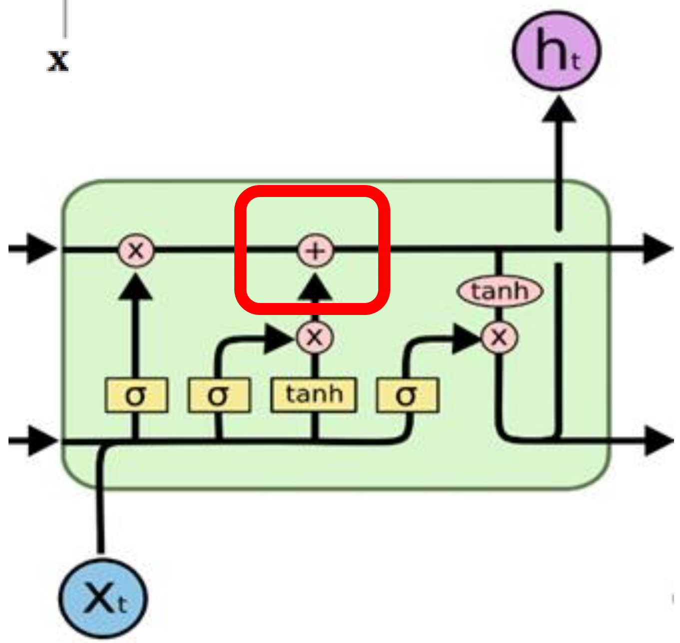
02 / 2024 https://openai.com/sora

Recap

- ❑ Ngram LM → Neural LM : sparsity
- ❑ Neural LM → RNN LM : input size is not scalable
- ❑ RNN LM → LSTM LM: vanishing gradients over time steps
- ❑ LSTM LM → Transformer : still vanishing gradients
- ❑ Transformer → Scaling up Transformer : scaling law!

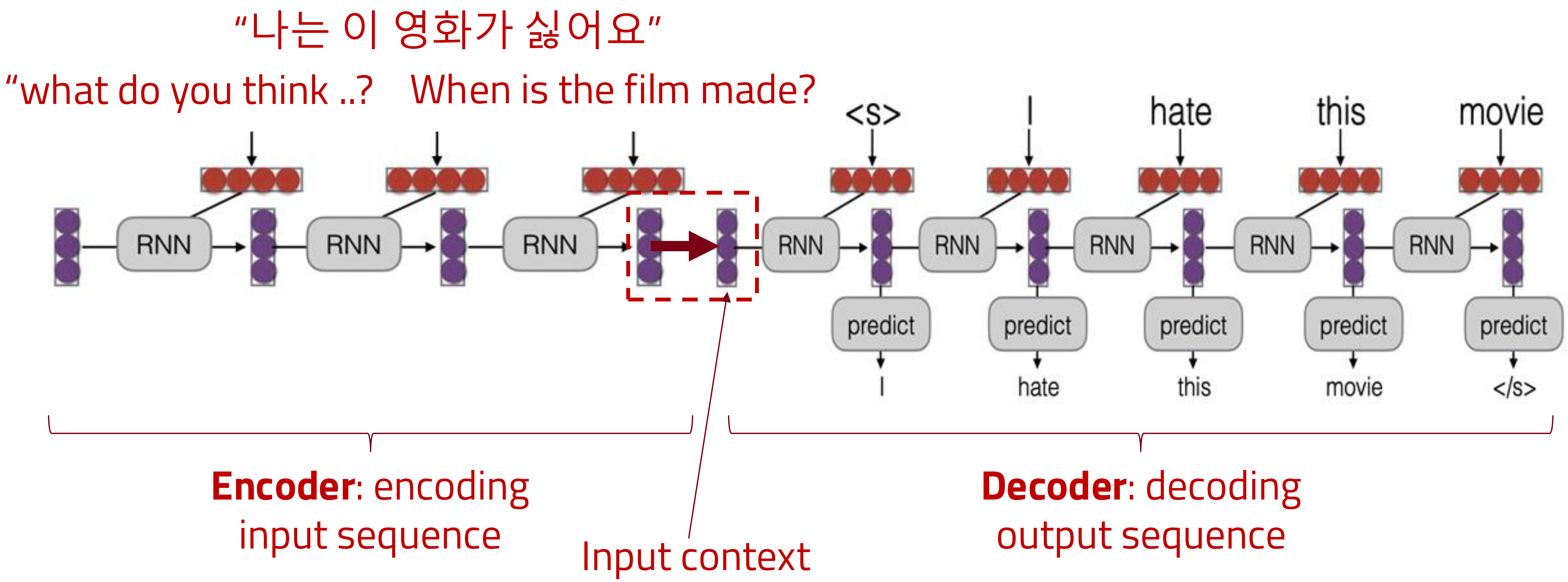


$$P(w) = P(w_i|context)$$
$$= softmax\,(W \cdot \boldsymbol{h_i})$$



Sequence-to-sequence modeling using RNN (encoder) - RNN (decoder)

Recap



State-of-the-art Language Models

Teaser: Transformer-based LMs

- ❑ SOTA LMs: GPT-2, Radford et al. 2018; GPT-3, Brown et al. 2020

Trigram	LSTM
109	58.3

GPT-2	GPT-3
35.8	20.5

Mar 19	Transformers (1) Project proposal due	• Attention is All you Need • Tutorial on Illustrated Transformer • Language Models are Unsupervised Multitask Learners
Mar 24	Transformers (2)	• Language Models are Few-Shot Learners • Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer

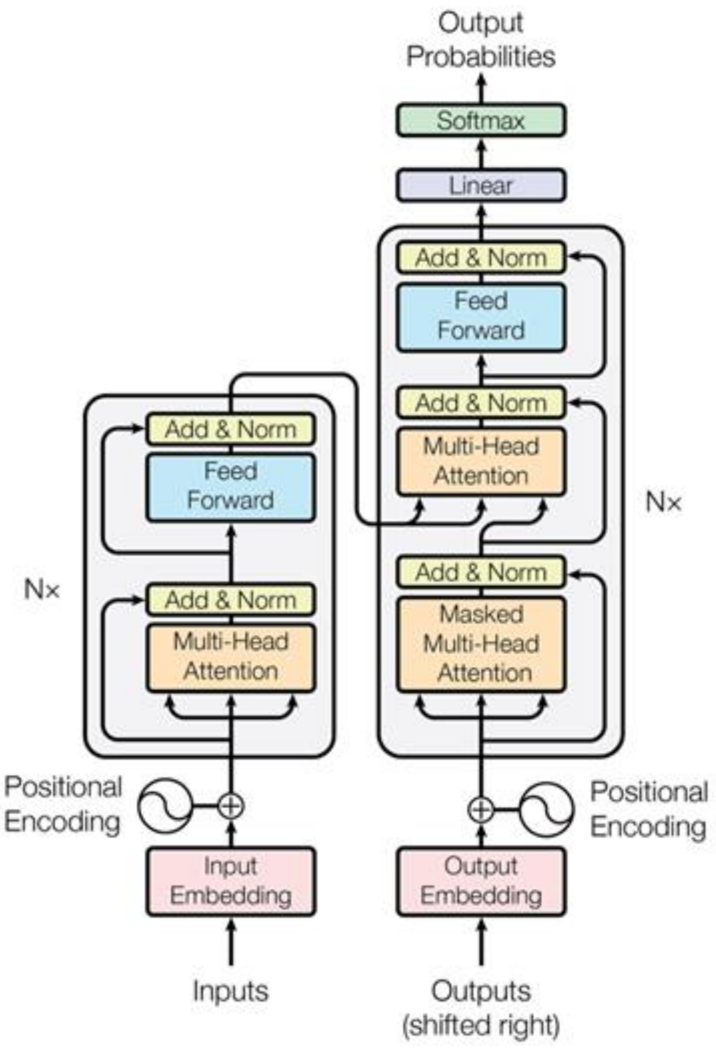
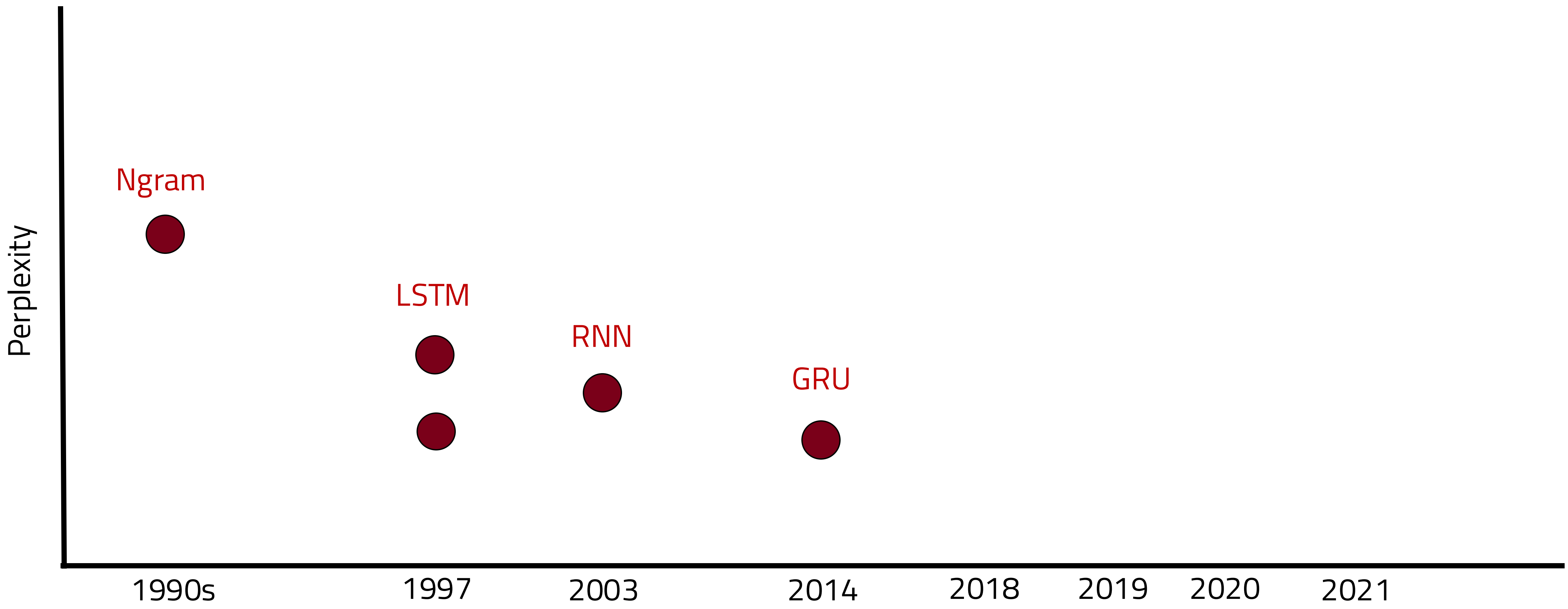
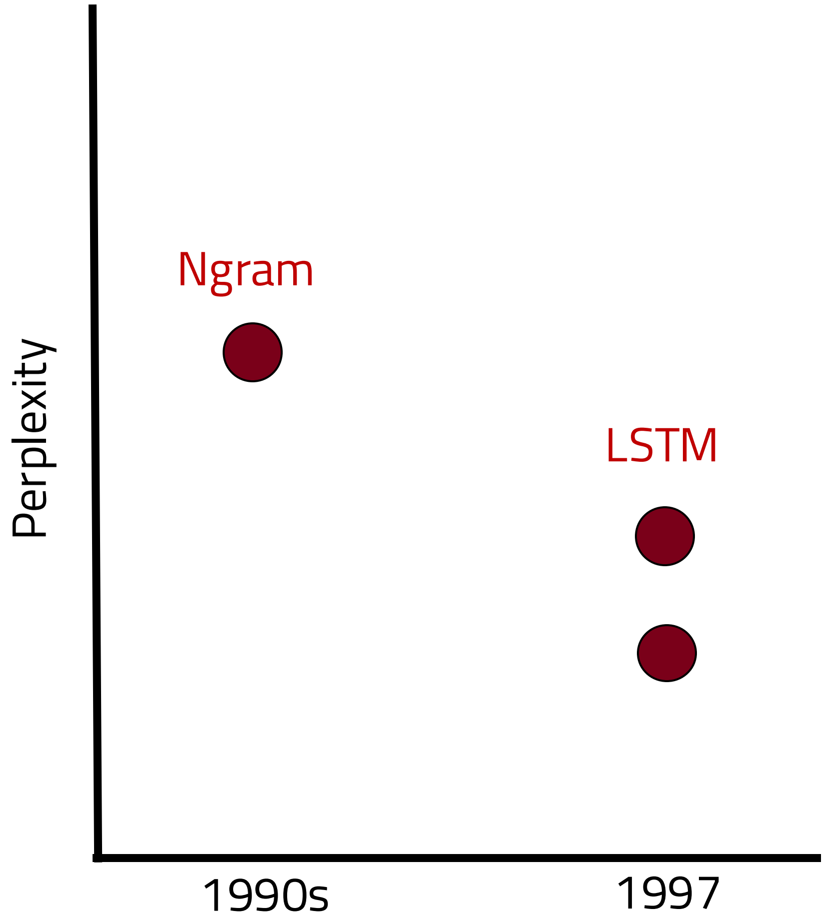


Figure 1: The Transformer - model architecture.


Perplexity
Ngram
LSTM
RNN
GRU
1990s
1997
2003
2014
2018
2019
2020
2021

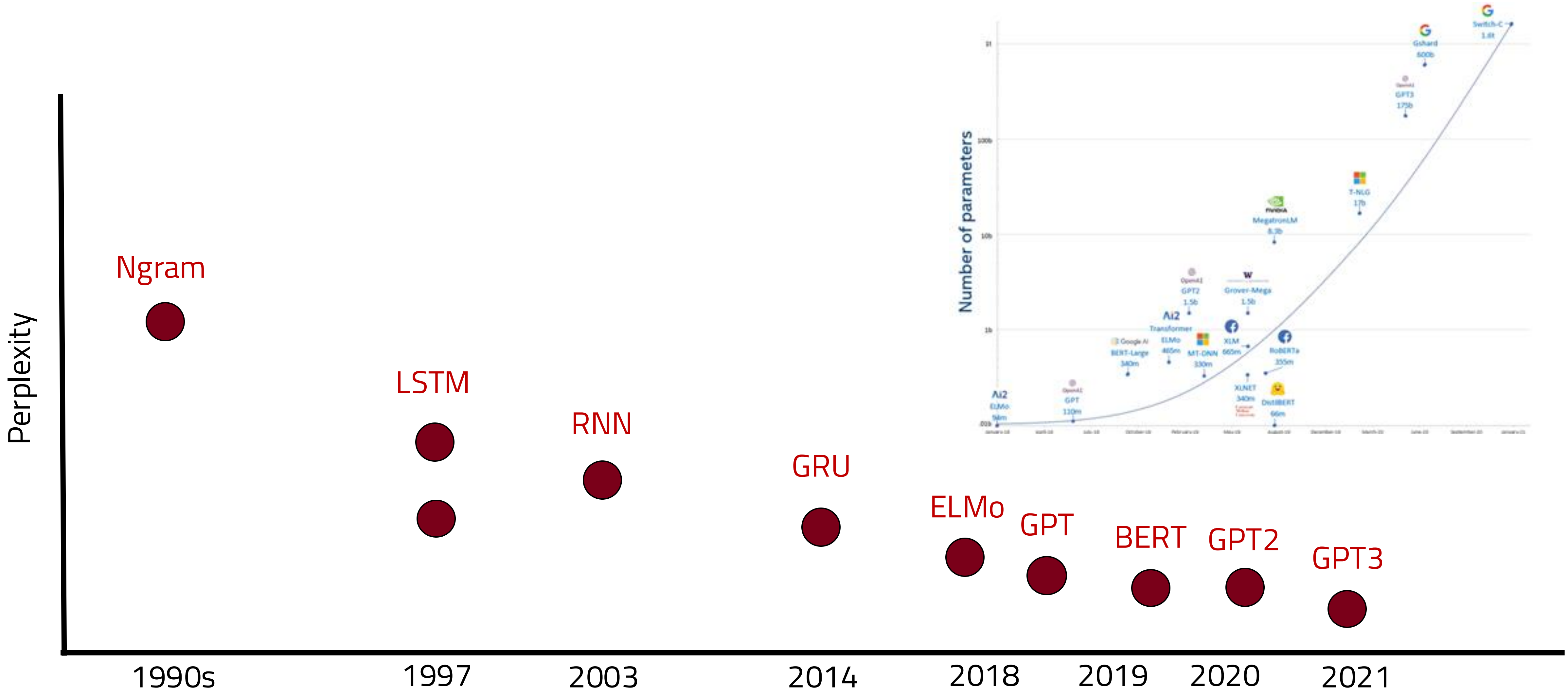


Jürgen Schmidhuber
Pronounce: You_again Shmidhoobuh
Technical Report IDSIA-23-23, IDSIA

AI Blog
Twitter: @SchmidhuberAI
14 December 2023

How 3 Turing Awardees Republished Key Methods and Ideas Whose Creators They Failed to Credit

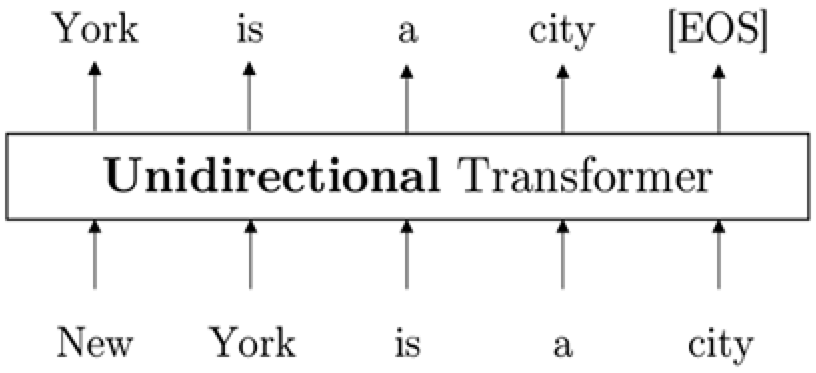
This write-up is meant to correct an inaccurate history of Artificial Intelligence (AI) propagated by recent uninformed news articles, posts in social media, and a large language model. Most of its statements are taken from a less streamlined report[T22] that has been reviewed on relevant AI mailing lists, profiting from feedback by many experts and well-known AI pioneers. **The piece is aimed at people who are not aware of the numerous AI priority disputes, but are willing to check the facts.**


Perplexity
Ngram
LSTM
RNN
GRU
ELMo
GPT
BERT
GPT2
GPT3
1990s
1997
2003
2014
2018
2019
2020
2021
Number of parameters

Teaser: Two Objectives for Language Model Pretraining

GPT GPT2 GPT3

Auto-regressive LM (GPT3)

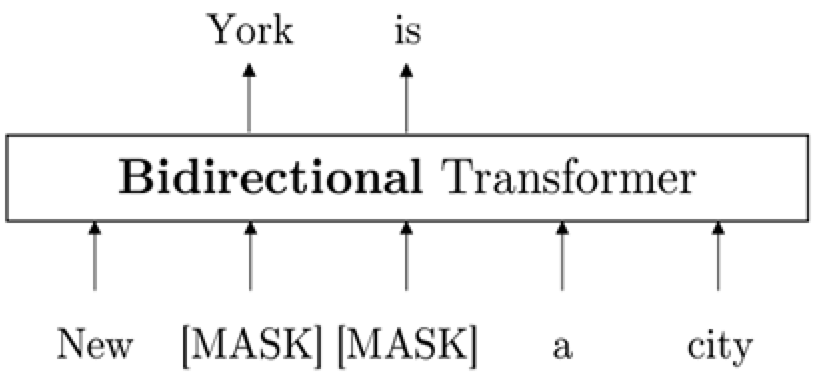


$$\log p(\mathbf{x}) = \sum_{t=1}^{T} \log p(x_t | \mathbf{x}_{<t})$$

Next-token prediction

ELMo BERT

Denoising autoencoding (BERT)



$$\log p(\bar{\mathbf{x}}|\hat{\mathbf{x}}) = \sum_{t=1}^{T} \text{mask}_t \log p(x_t | \hat{\mathbf{x}})$$

Reconstruct masked tokens

Slides from Zihang Dai

Why better language models are useful?

Language models can directly encode knowledge present in the training corpus.

The director of 2001: A Space Odyssey is ______________

Language models can directly encode knowledge present in the training corpus.

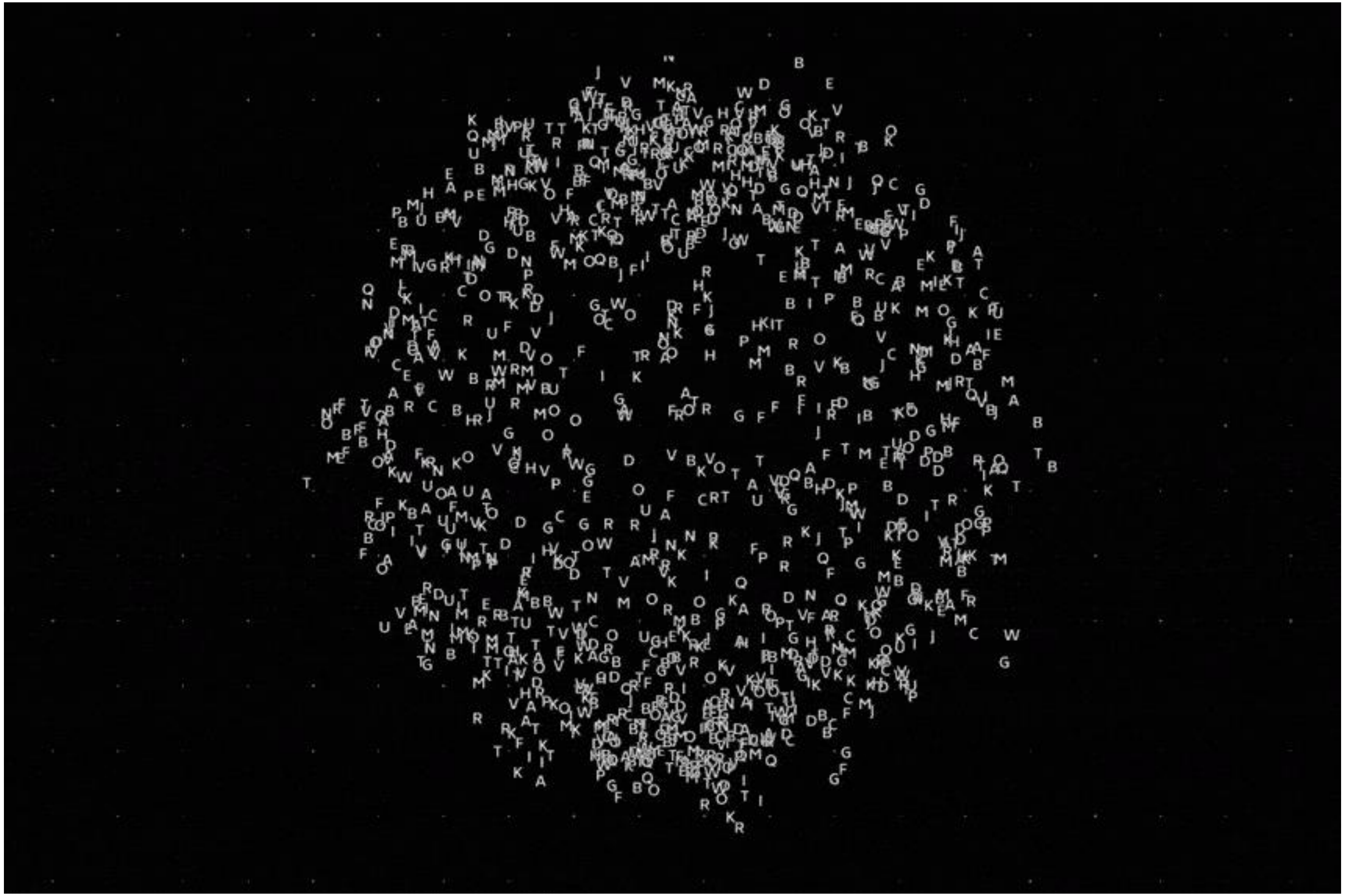
Query	Answer	Generation
Francesco Bartolomeo Conti was born in ____.	Florence	Rome [-1.8] , **Florence [-1.8]** , Naples

Petroni et al. (2019), "Language Models as Knowledge Bases?" (ACL)

Language models can directly encode knowledge present in the training corpus.

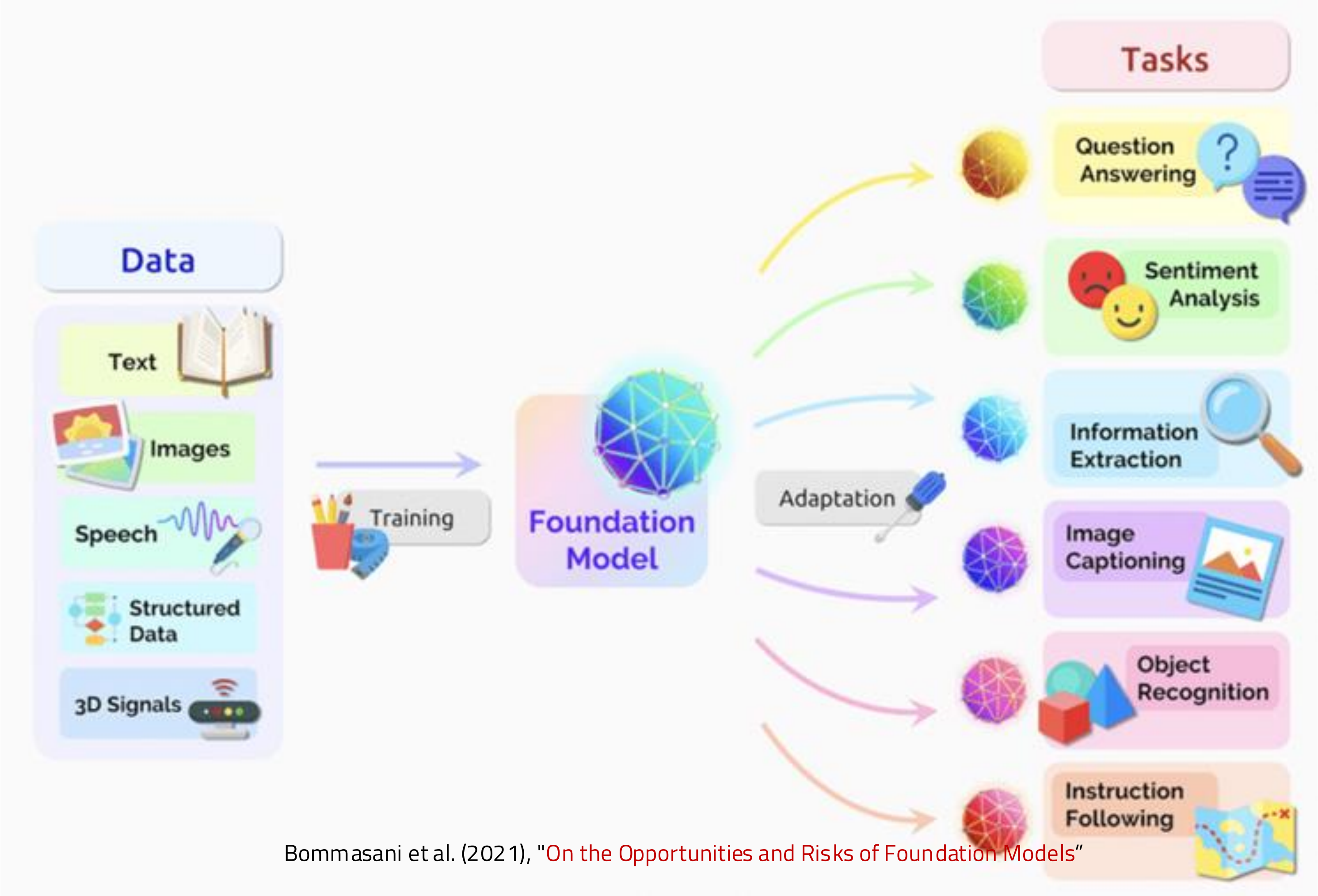
Query	Answer	Generation
Francesco Bartolomeo Conti was born in ____.	Florence	Rome [-1.8] , **Florence** **[-1.8]** , Naples
Adolphe Adam died in ____.	Paris	**Paris** **[-0.5]** , London [-3.5] , Vienna
English bulldog is a subclass of ____.	dog	dogs [-0.3] , breeds [-2.2] , **dog**
The official language of Mauritius is ____.	English	**English** **[-0.6]** , French [-0.9] , Arabic
Patrick Oboya plays in ____ position.	midfielder	centre [-2.0] , center [-2.2] , **midfielder**
Hamburg Airport is named after ____.	Hamburg	Hess [-7.0] , Hermann [-7.1] , Schmidt

Petroni et al. (2019), "Language Models as Knowledge Bases?" (ACL)



ChatGPT Is a Blurry JPEG of the Web, By Ted Chiang February 9, 2023

Language models can be a foundation for various tasks across different modalities



Bommasani et al. (2021), "On the Opportunities and Risks of Foundation Models"

Language models are stochastic parrots

Bender et al. (2021), "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?"

Questions

- GPT3 is 100x bigger than GPT2. If GPT-K is developed, how can we handle such a large-scale model without industry-level computing powers. Can we compress the models while not sacrificing performance?
- What if those companies can only replicate the results, monopolize their usages, and make them as a paid service? Is it fair?
- Are there different ways of storing the predictive/knowledge power of LMs?
- Can LMs be called as general intelligence or foundational knowledge? If not, what are missing there?