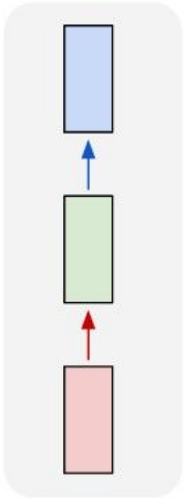
Обработка естественного языка: RNN, LSTM, Seq2seq

Языковые модели (LM)

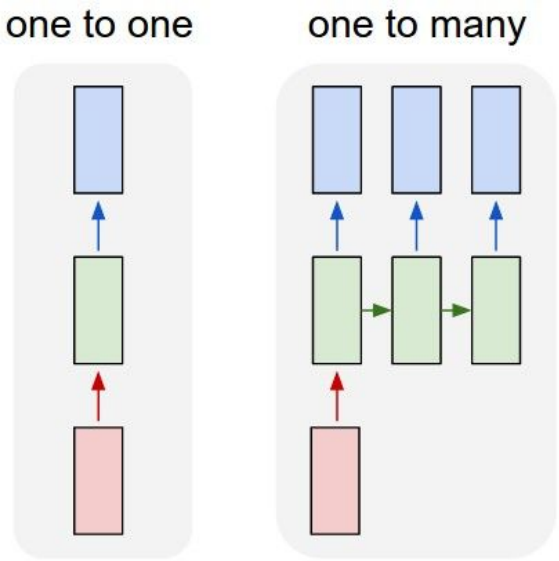
“Vanilla” Neural Network

one to one



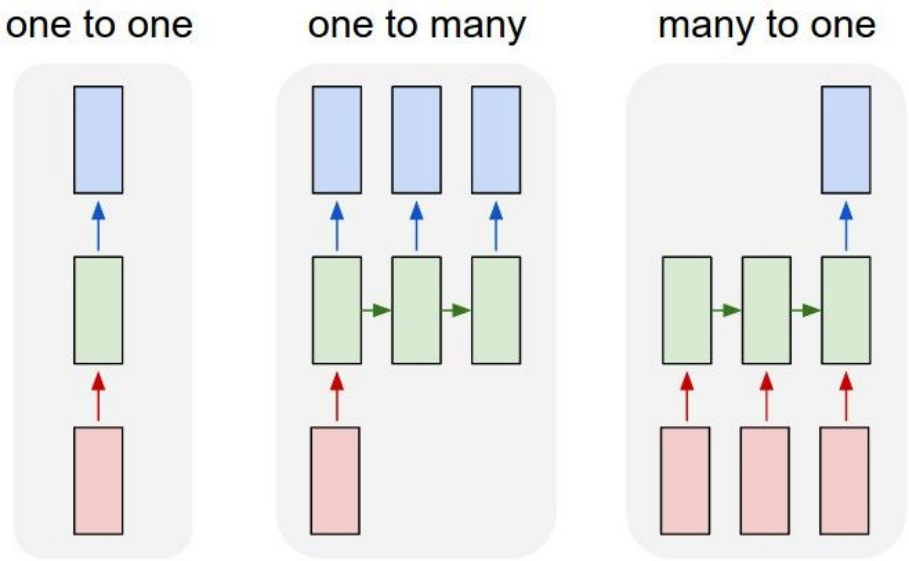
Vanilla Neural Networks

Recurrent Neural Networks: Process Sequences



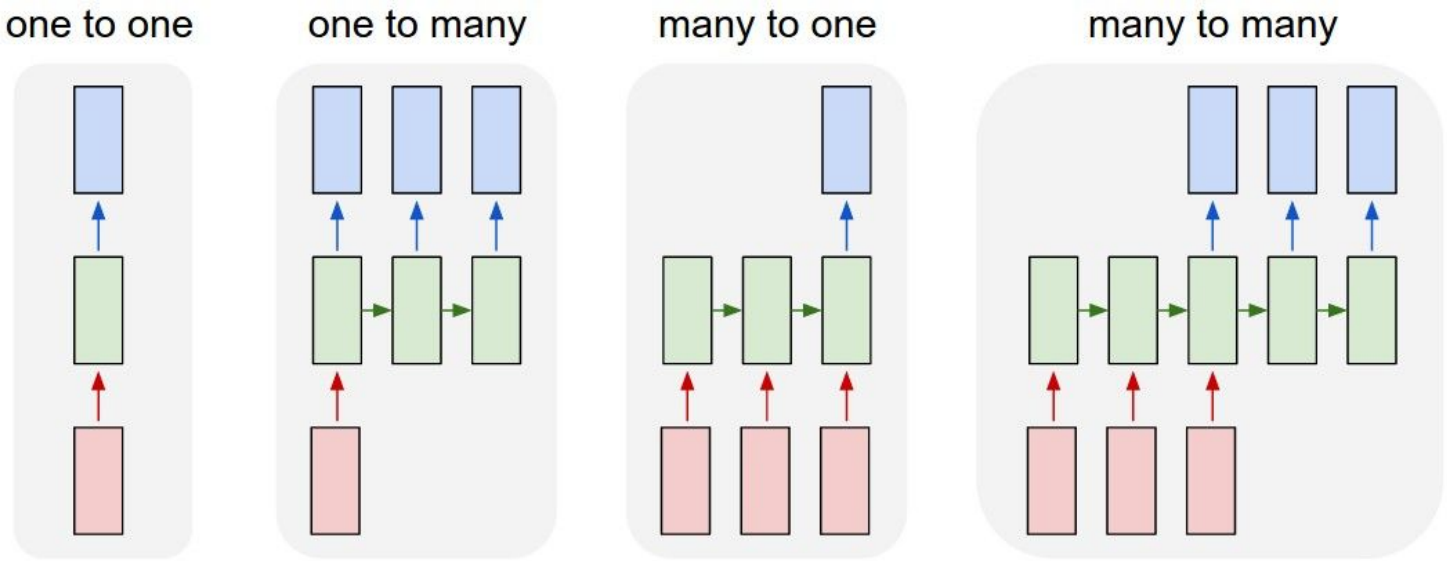
e.g. **Image Captioning**
image -> sequence of words

Recurrent Neural Networks: Process Sequences



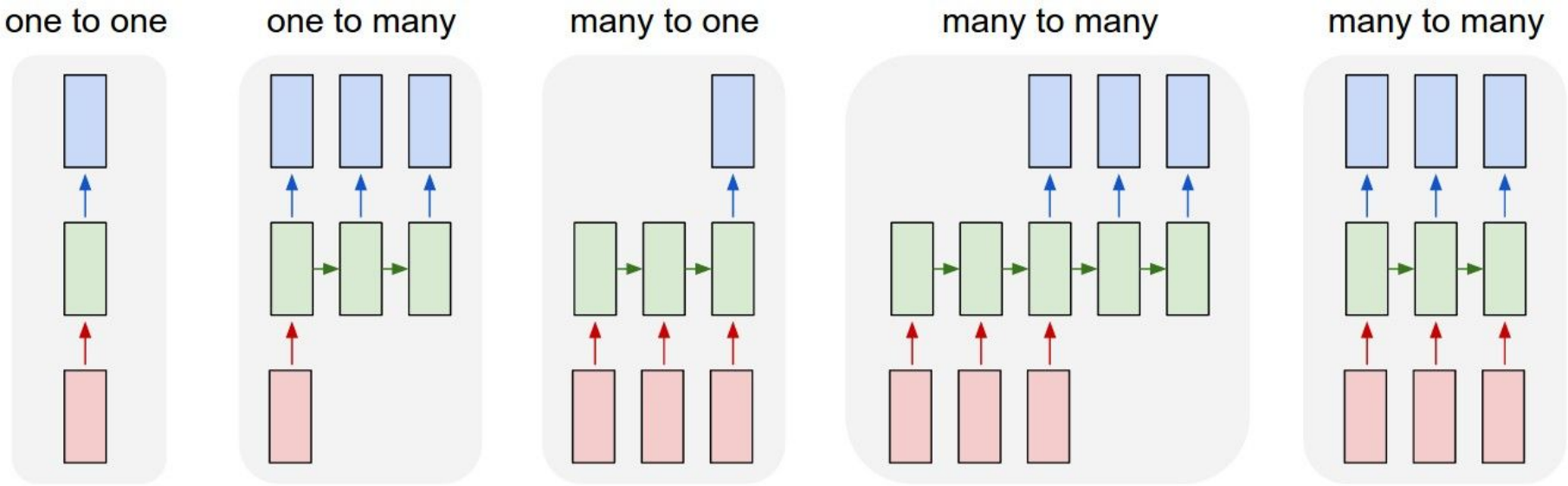
e.g. **action prediction**
sequence of video frames -> action class

Recurrent Neural Networks: Process Sequences



E.g. **Video Captioning**
Sequence of video frames -> caption

Recurrent Neural Networks: Process Sequences



e.g. **Video classification on frame level**

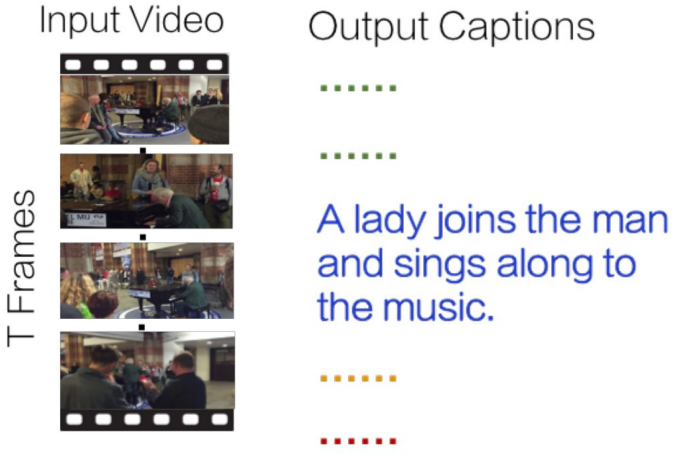
Why existing convnets are insufficient?

Variable sequence length inputs and outputs!

Example task: video captioning

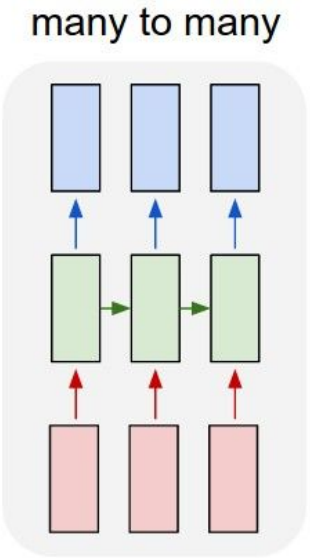
Input video can have variable number of frames

Output captions can be variable length.

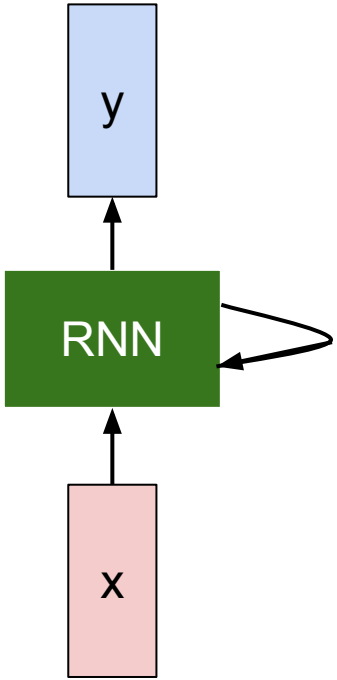


Krishna, Hata, Ren, Fei-Fei, Niebles. Dense captioning Events in Videos. ICCV 2019

Let's start with a task that takes a variable input and produces an output at every step



Recurrent Neural Network



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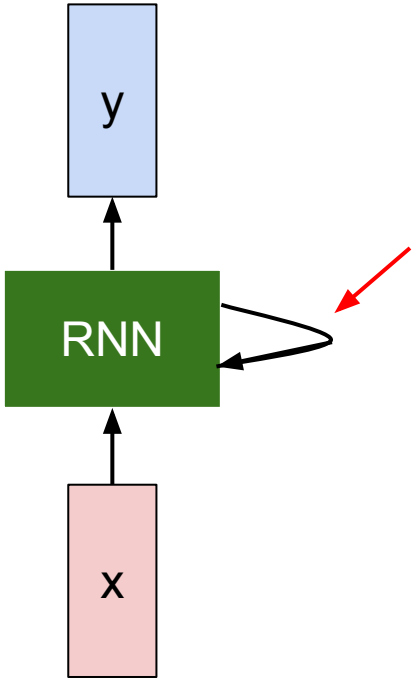
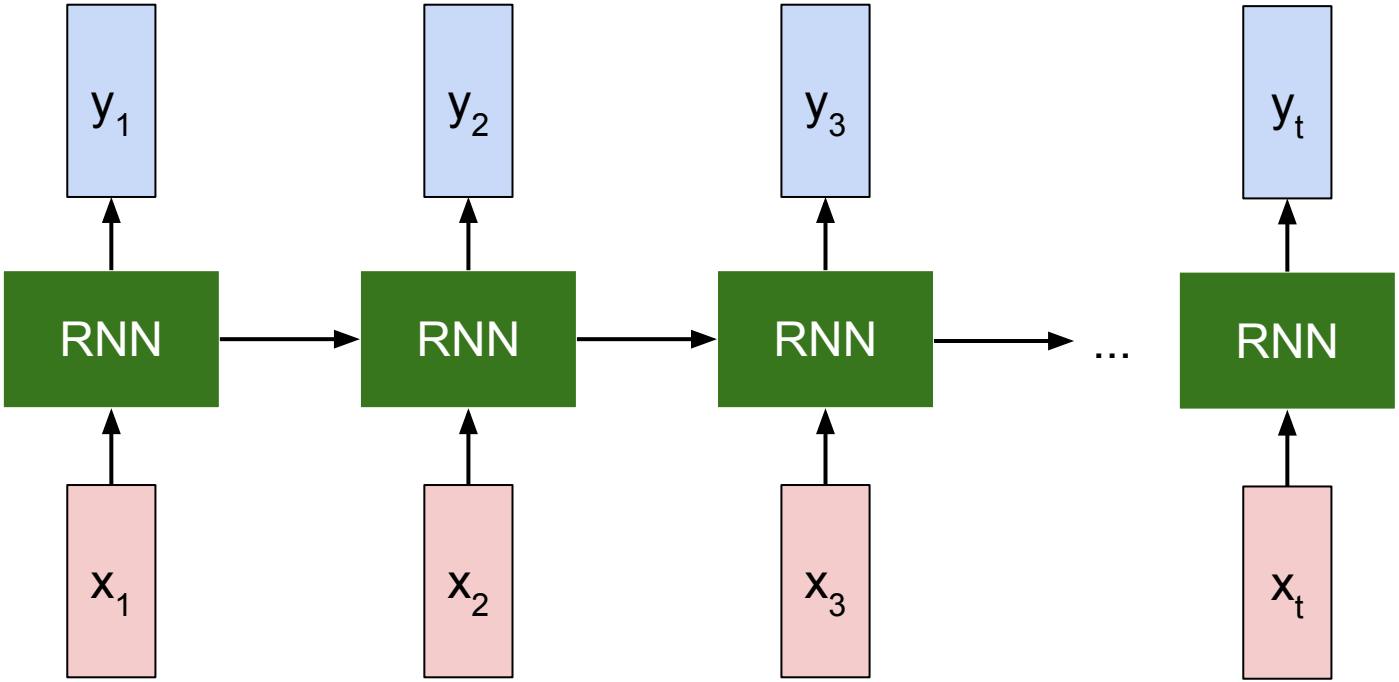


Key idea: RNNs have an "internal state" that is updated as a sequence is processed

Unrolled RNN



RNN hidden state update

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

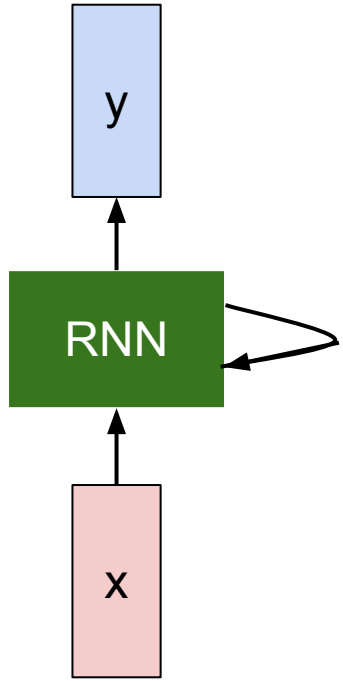
$$h_t = f_W(h_{t-1}, x_t)$$

new state

some function with parameters W

old state

input vector at some time step



RNN output generation

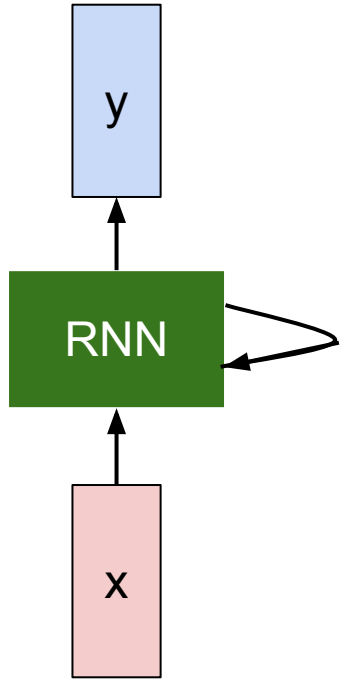
We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

$$y_t = f_{W_{hy}}(h_t)$$

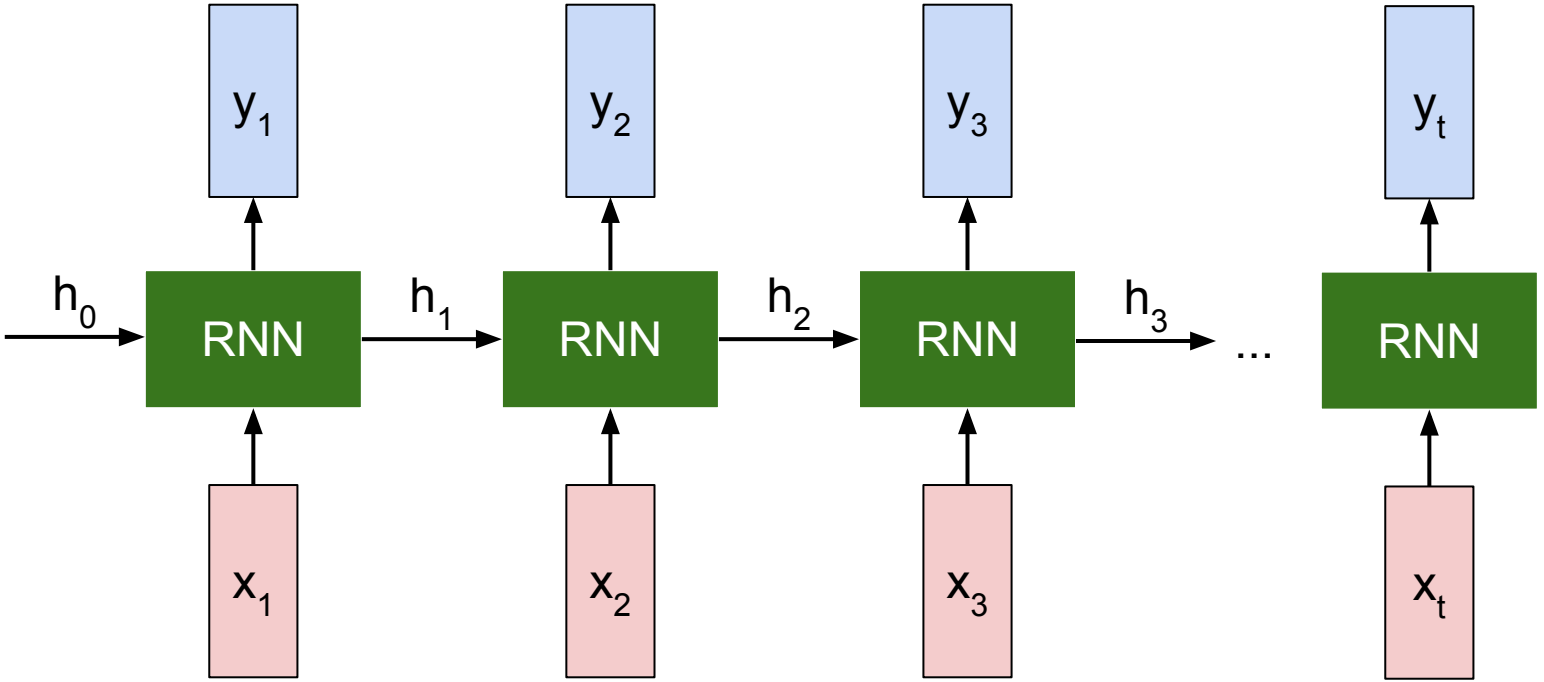
output

new state

another function with parameters W_o



Recurrent Neural Network



Recurrent Neural Network

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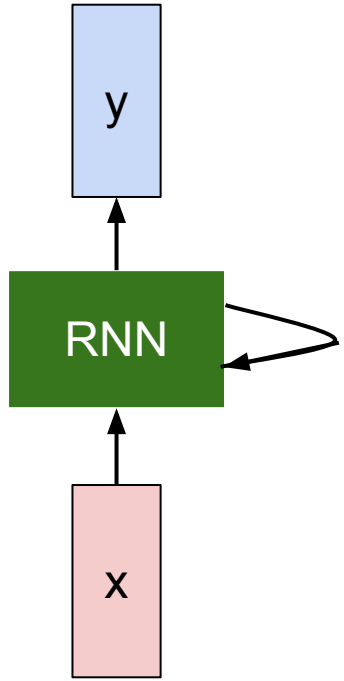
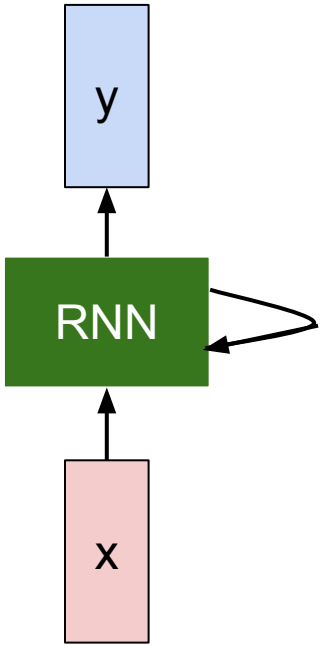


Notice: the same function and the same set of parameters are used at every time step.

(Simple) Recurrent Neural Network

The state consists of a single *"hidden"* vector **h**:



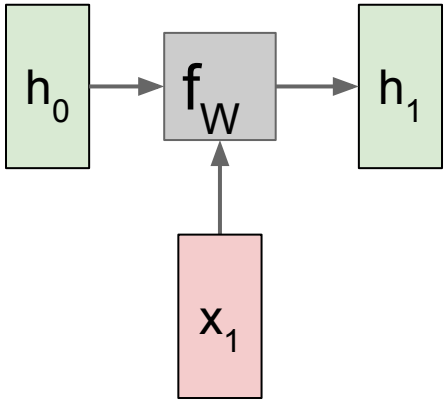
$$h_t = f_W(h_{t-1}, x_t)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

Sometimes called a "Vanilla RNN" or an "Elman RNN" after Prof. Jeffrey Elman

RNN: Computational Graph

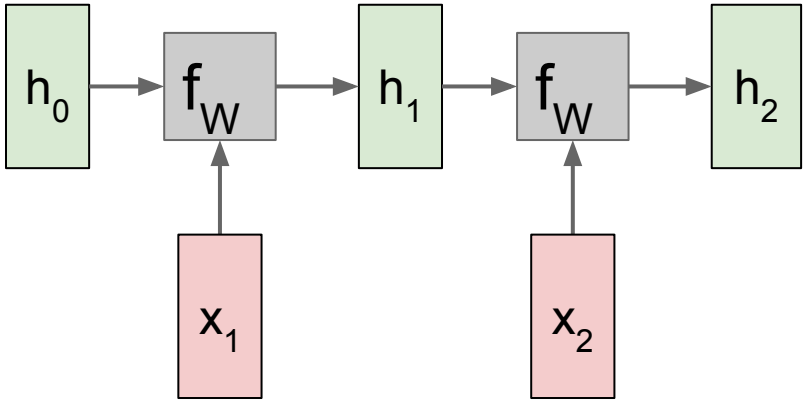


Tanh (гиперболический тангенс) — это функция активации, часто используемая в нейронных сетях, особенно в рекуррентных нейронных сетях (RNN). Она принимает значения на входе и "сжимает" их в диапазон от -1 до 1.

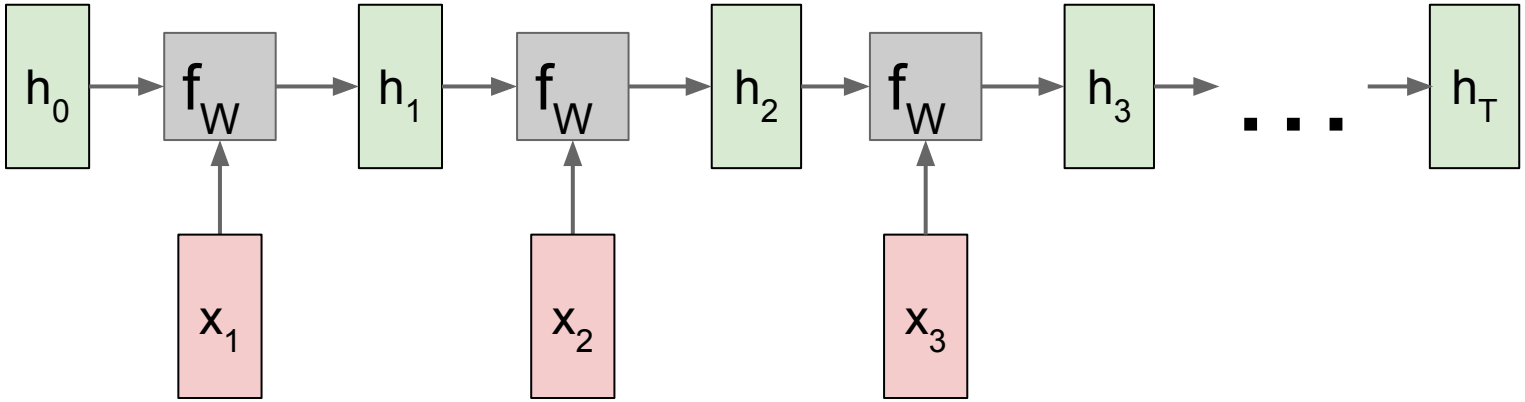
Whx — матрица весов для входа, связывает текущий вход xtxt с текущим скрытым состоянием htht.

Whh — матрица весов для скрытого состояния, связывает скрытое состояние на предыдущем временном шаге ht−1ht−1 с текущим скрытым состоянием htht

RNN: Computational Graph

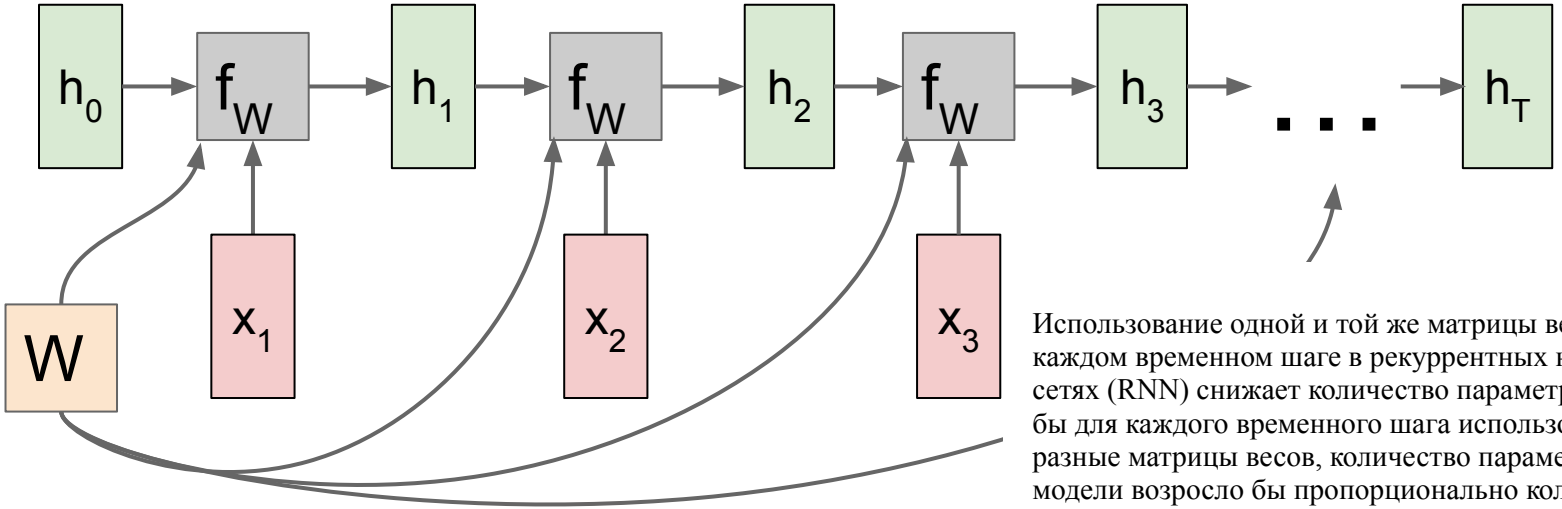


RNN: Computational Graph



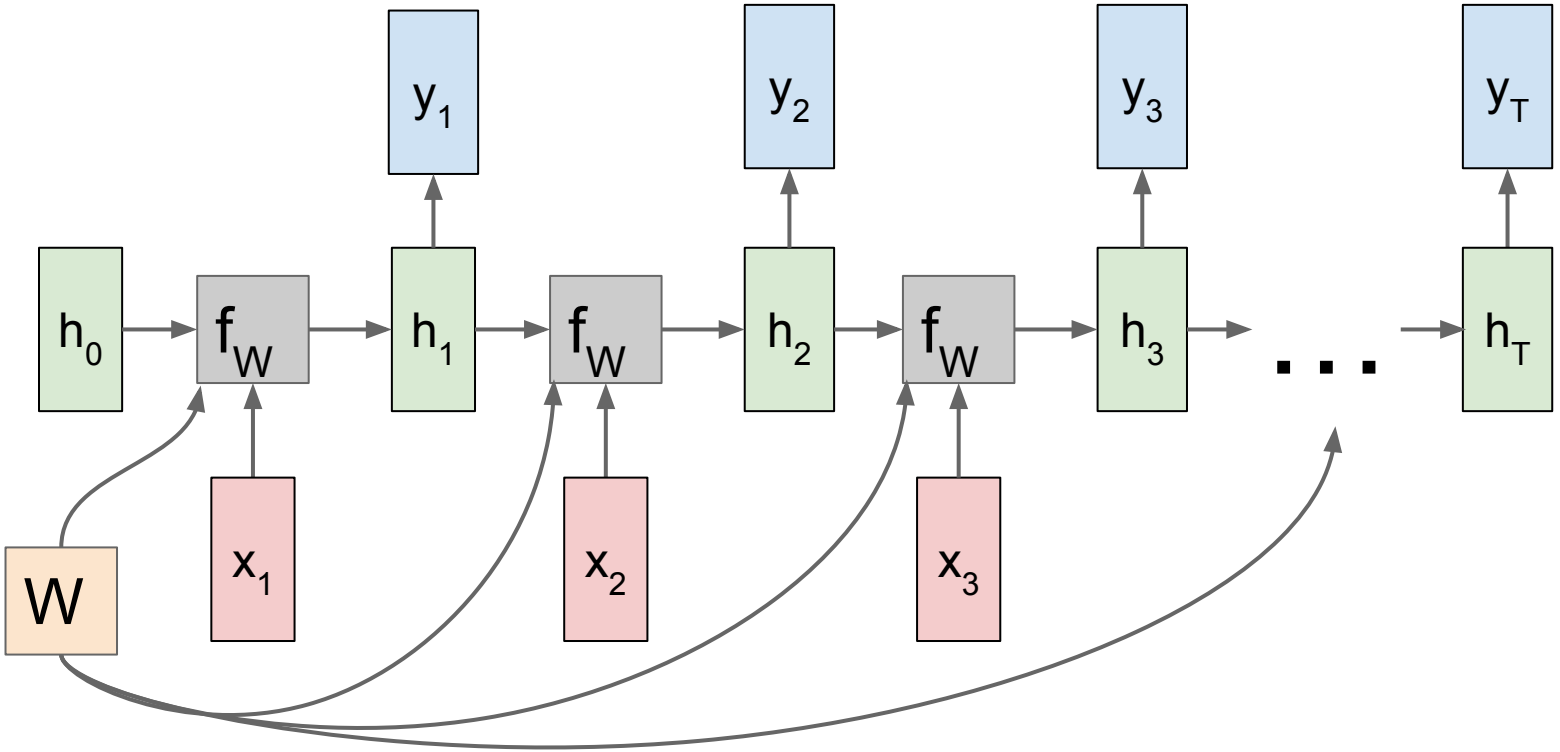
RNN: Computational Graph

Re-use the same weight matrix at every time-step



Использование одной и той же матрицы весов на каждом временном шаге в рекуррентных нейронных сетях (RNN) снижает количество параметров: Если бы для каждого временного шага использовались разные матрицы весов, количество параметров в модели возросло бы пропорционально количеству временных шагов. Это сделало бы обучение модели более ресурсоемким и сложным.

RNN: Computational Graph: Many to Many



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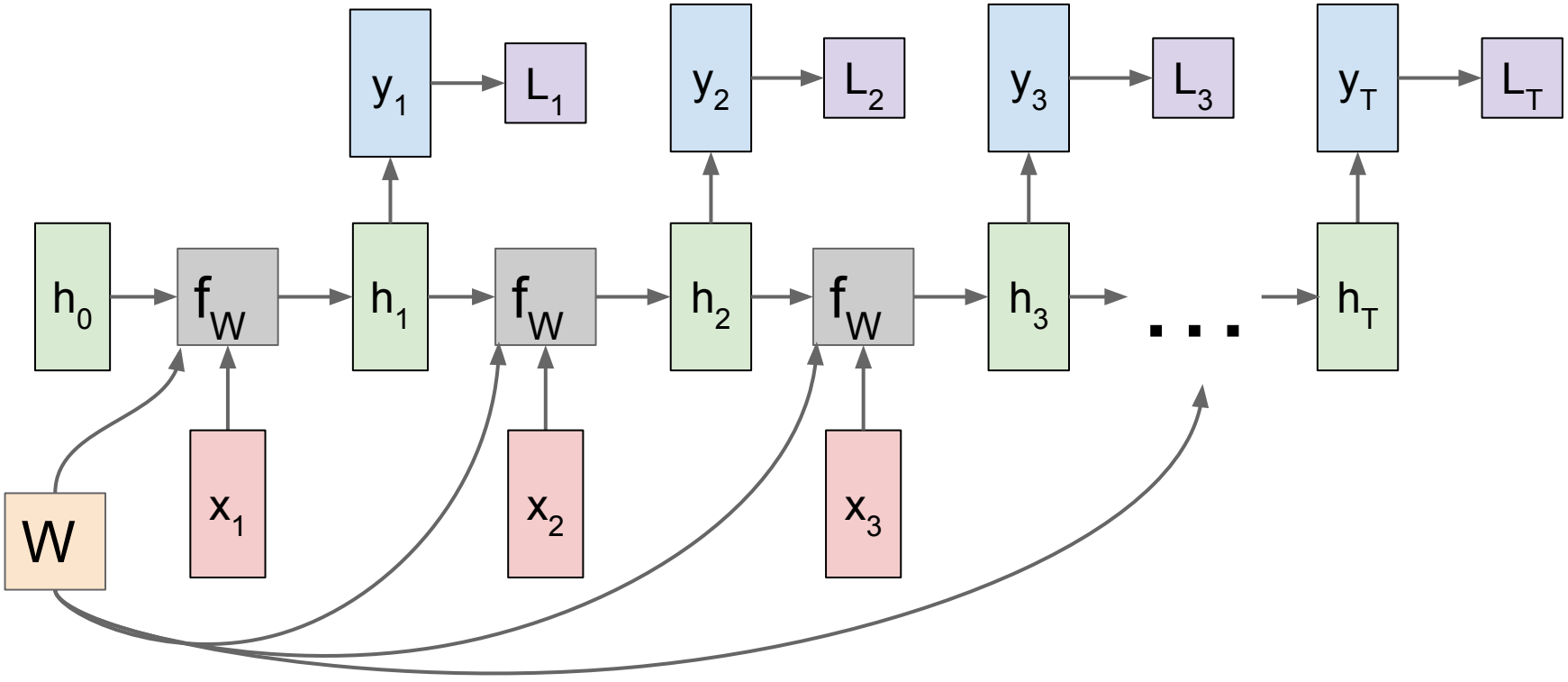

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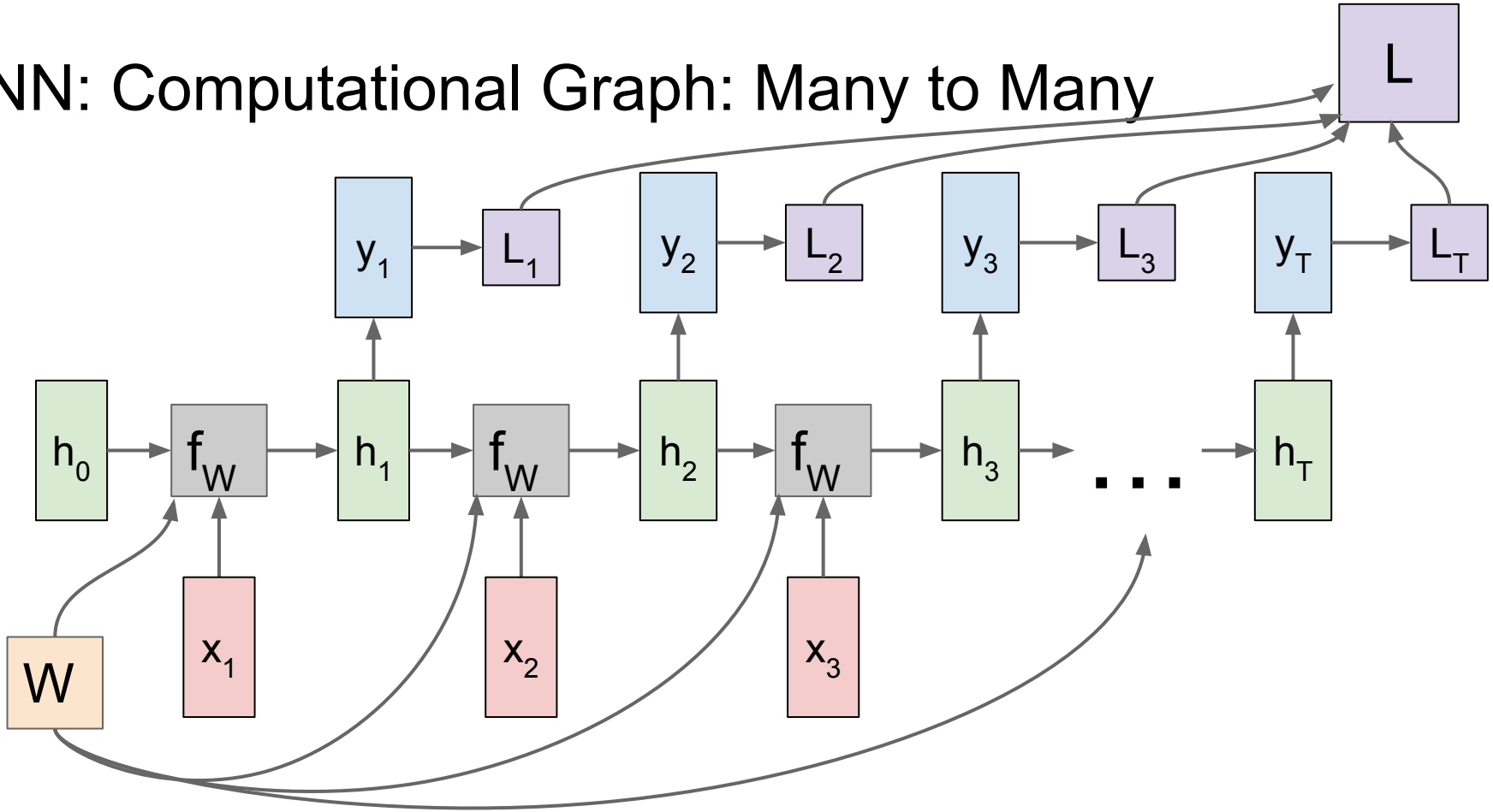
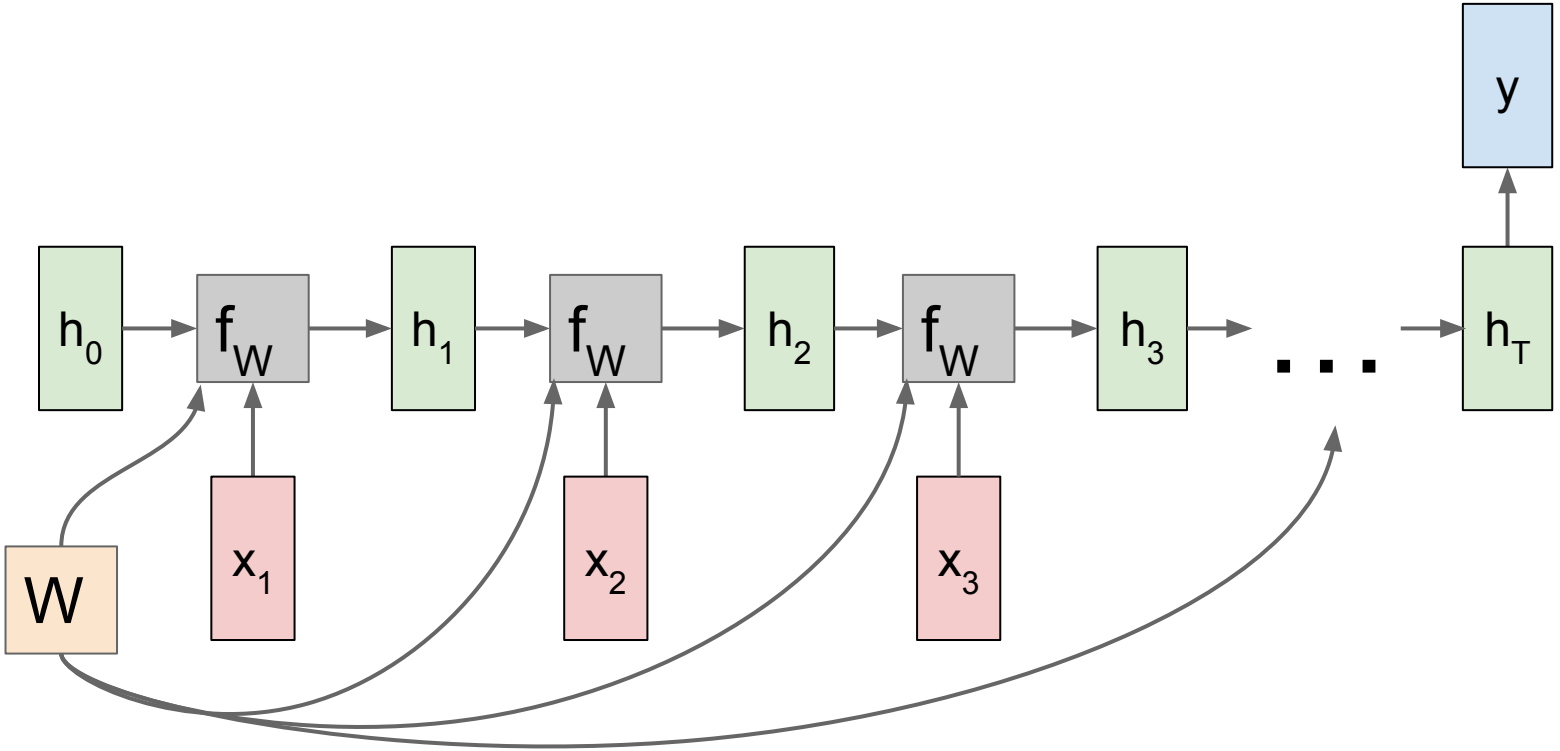


RNN: Computational Graph: Many to One



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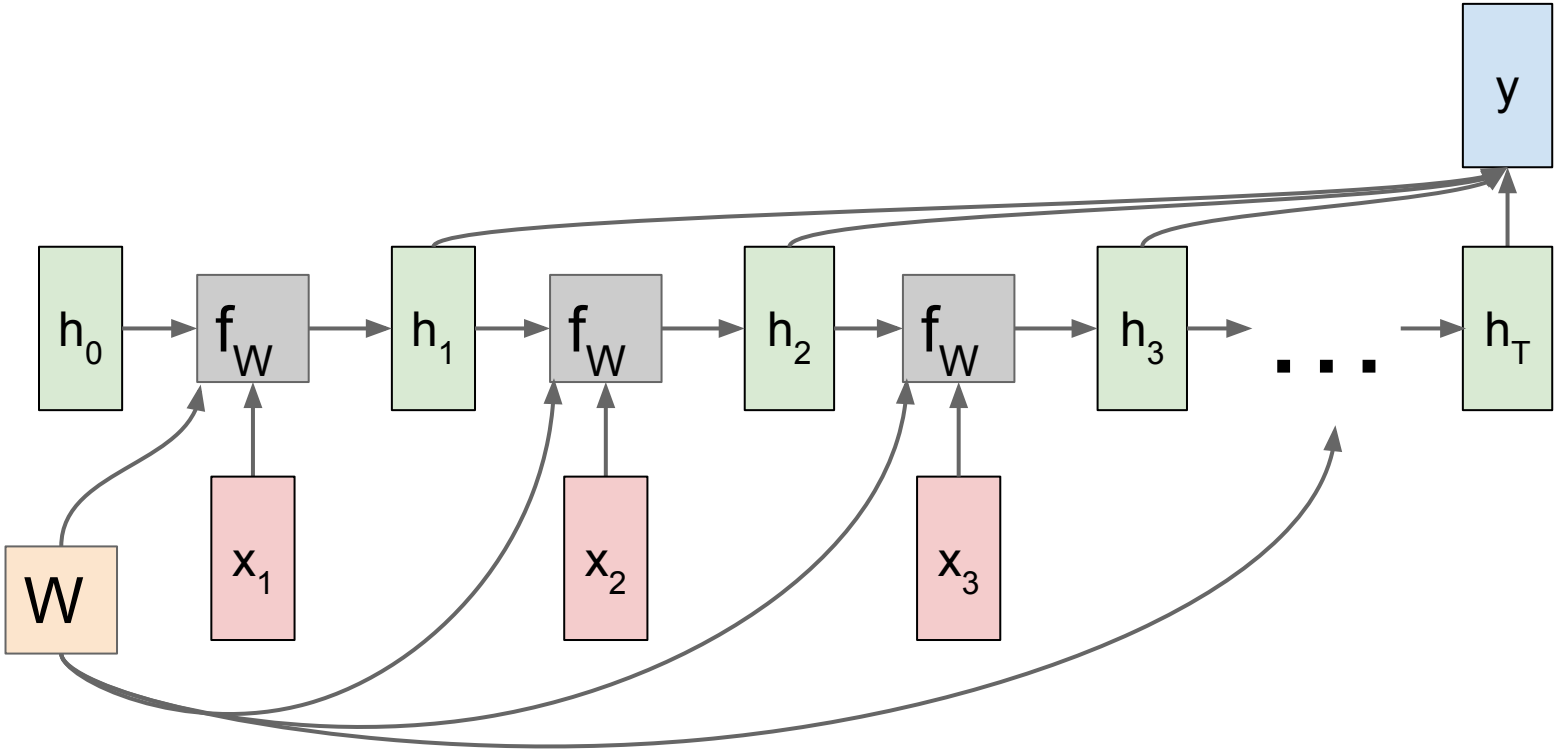
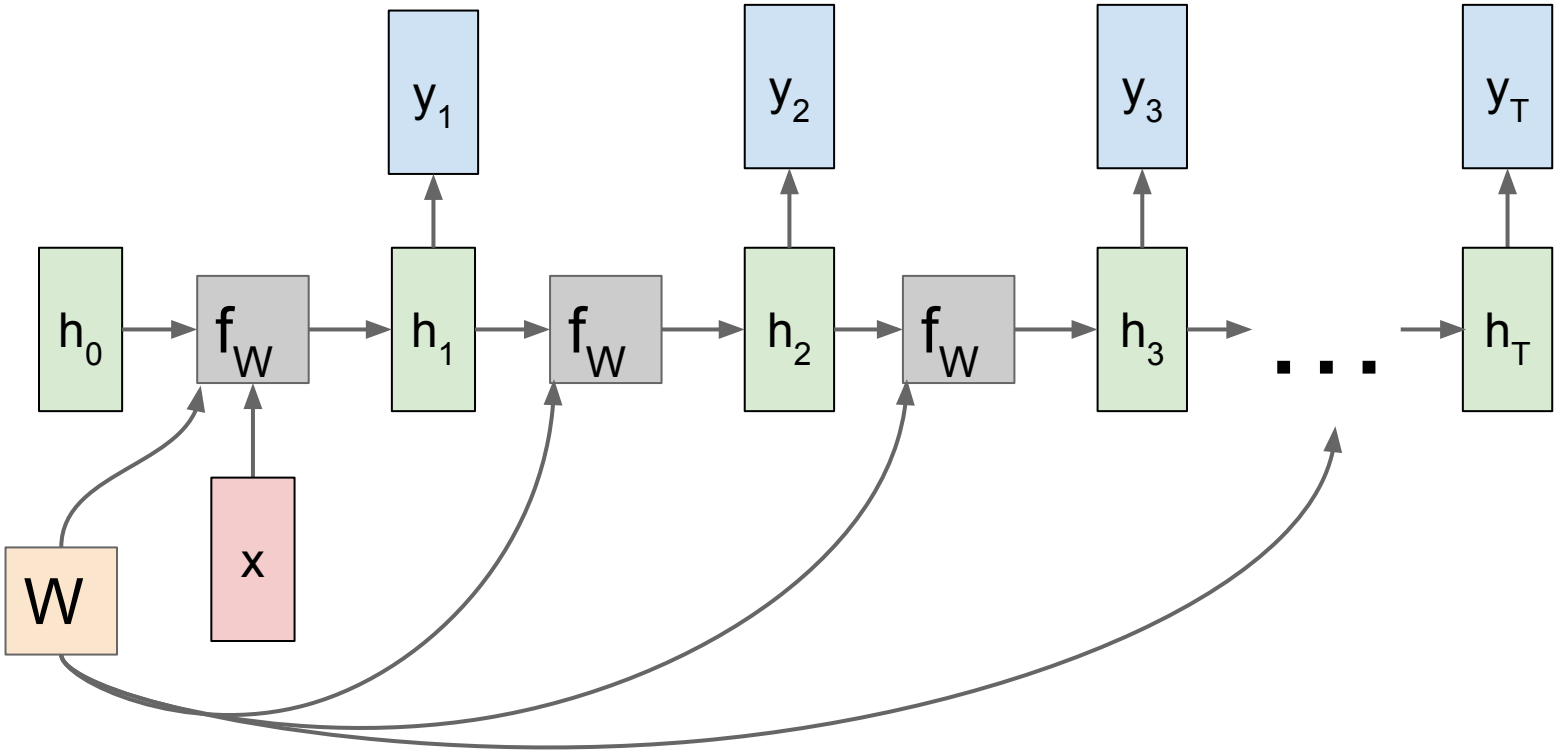


RNN: Computational Graph: One to Many



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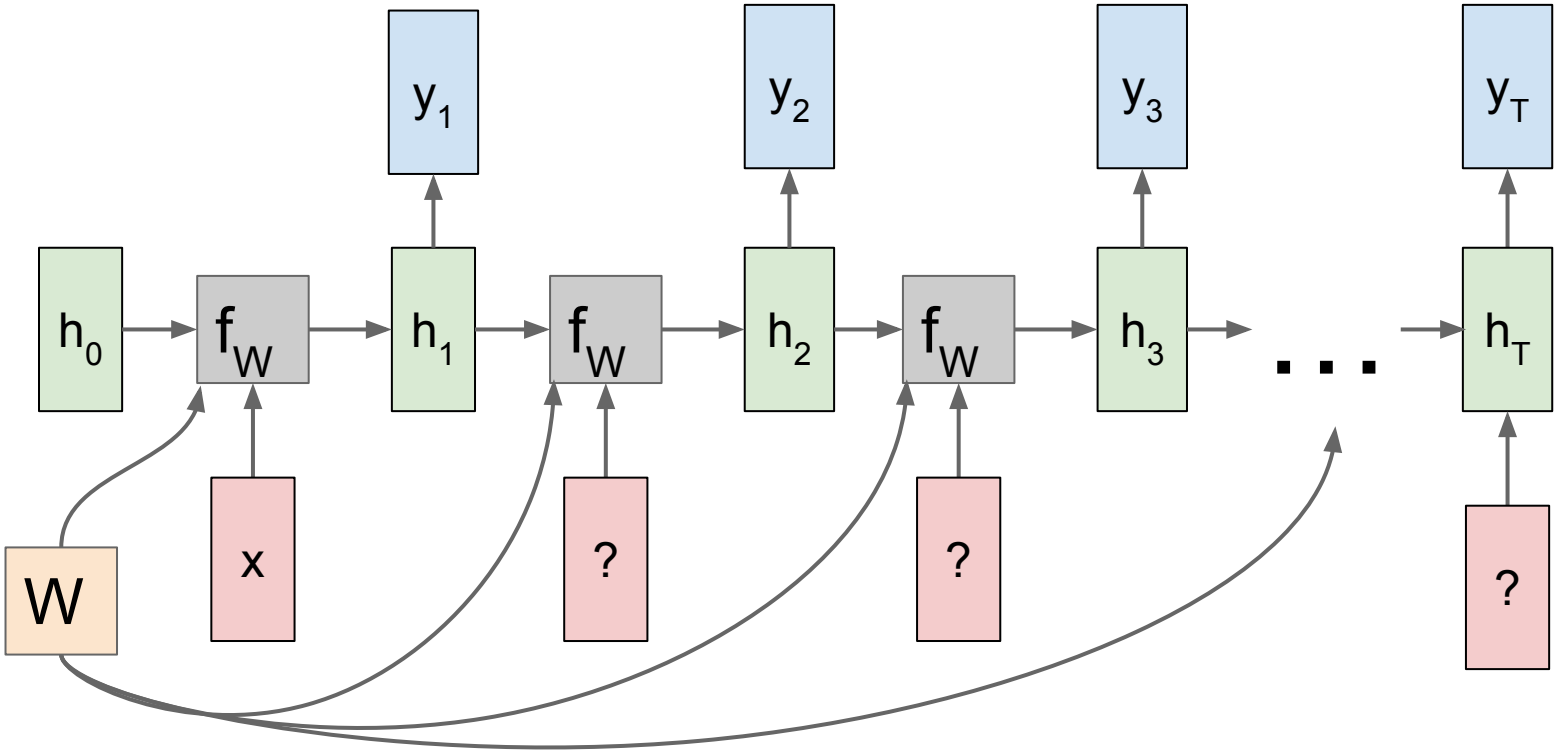

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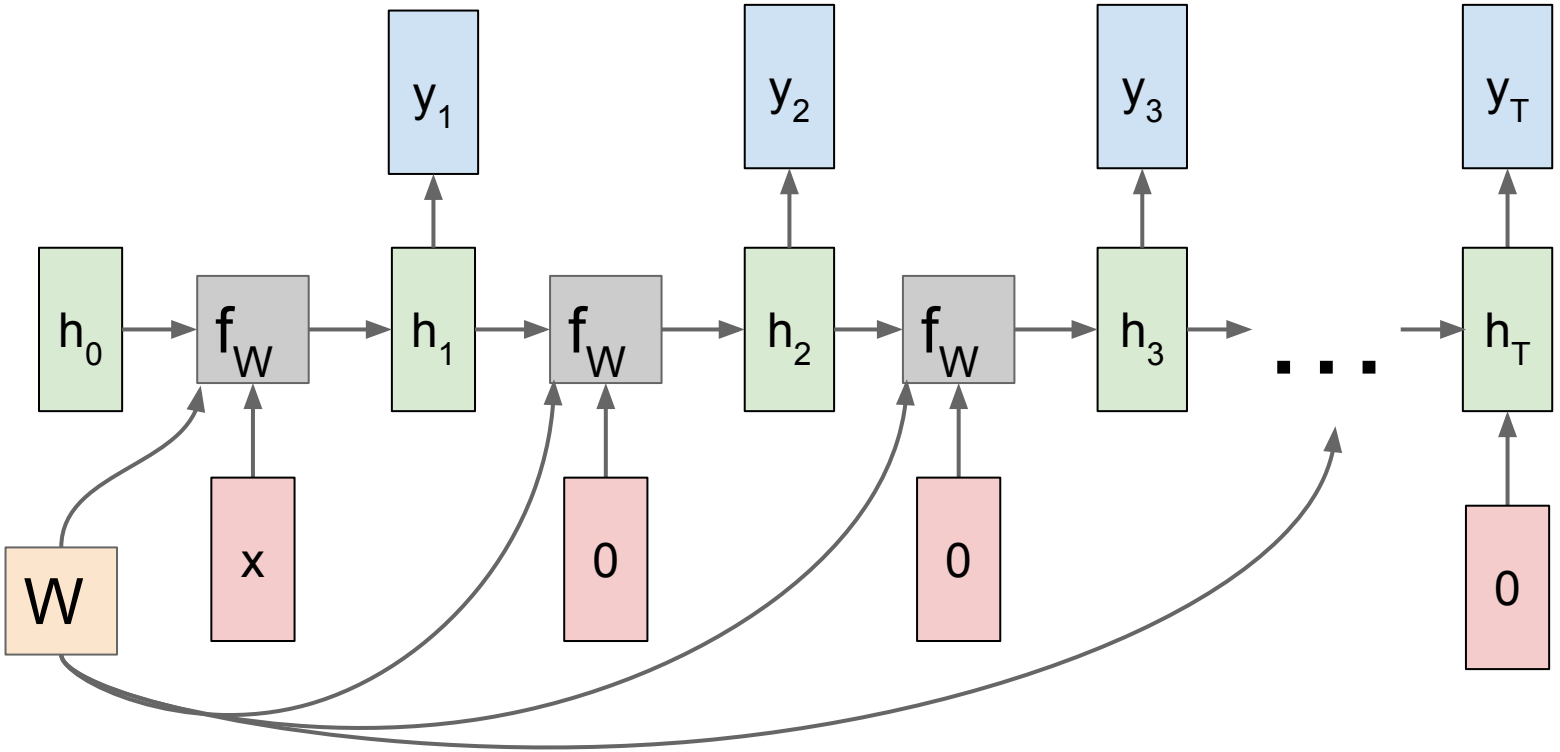

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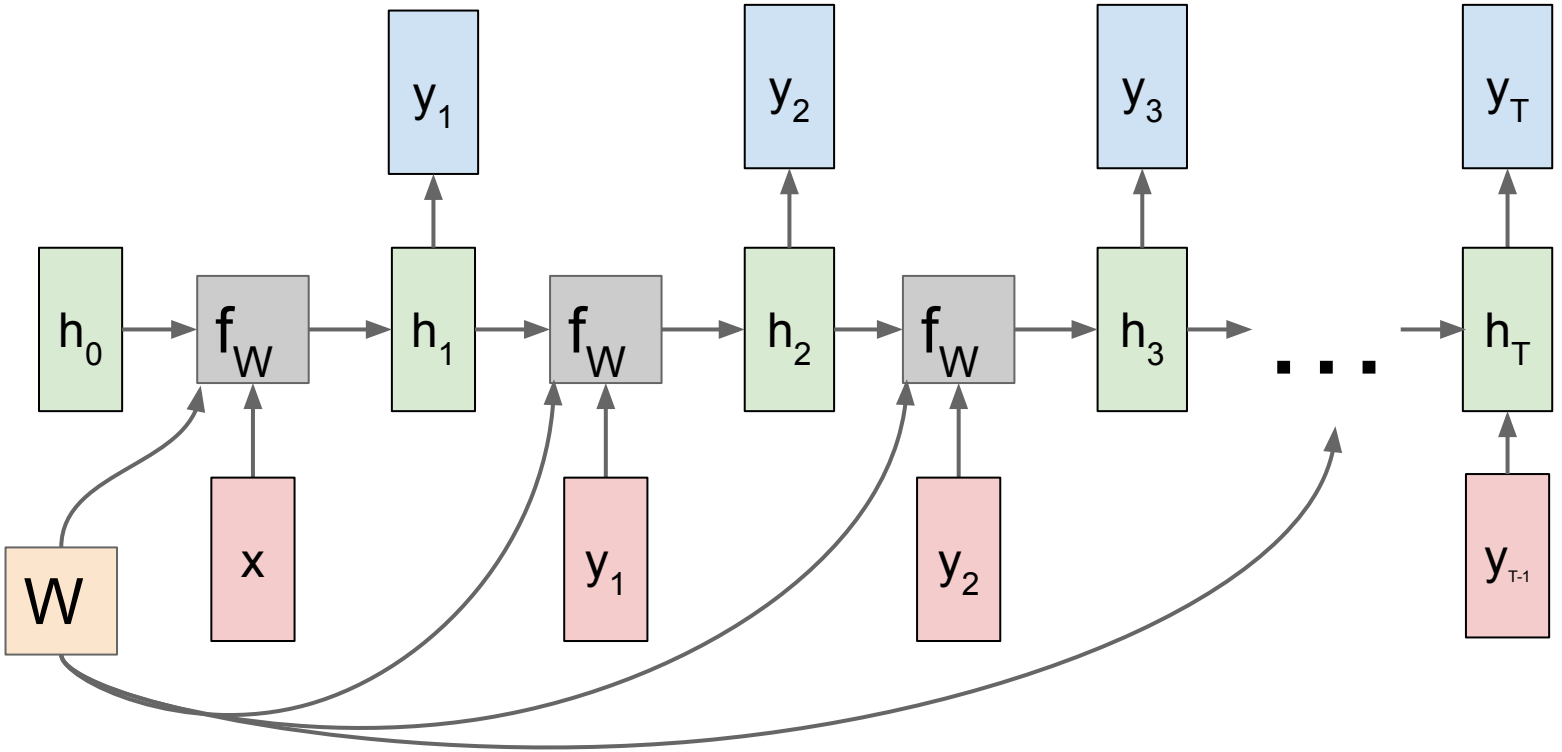
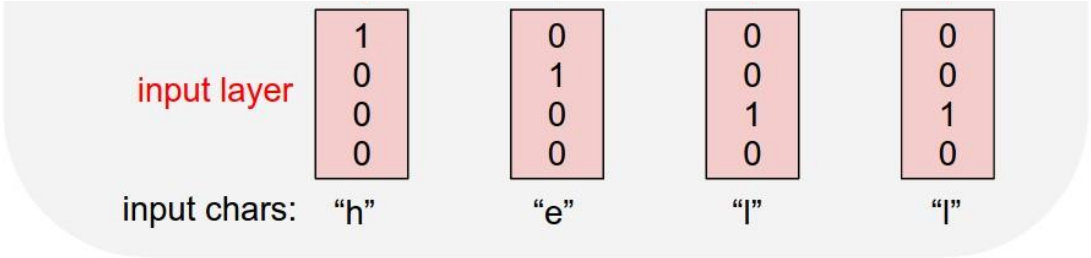


Example: Character-level Language Model

Vocabulary:
[h,e,l,o]

Example training sequence:
“hello”



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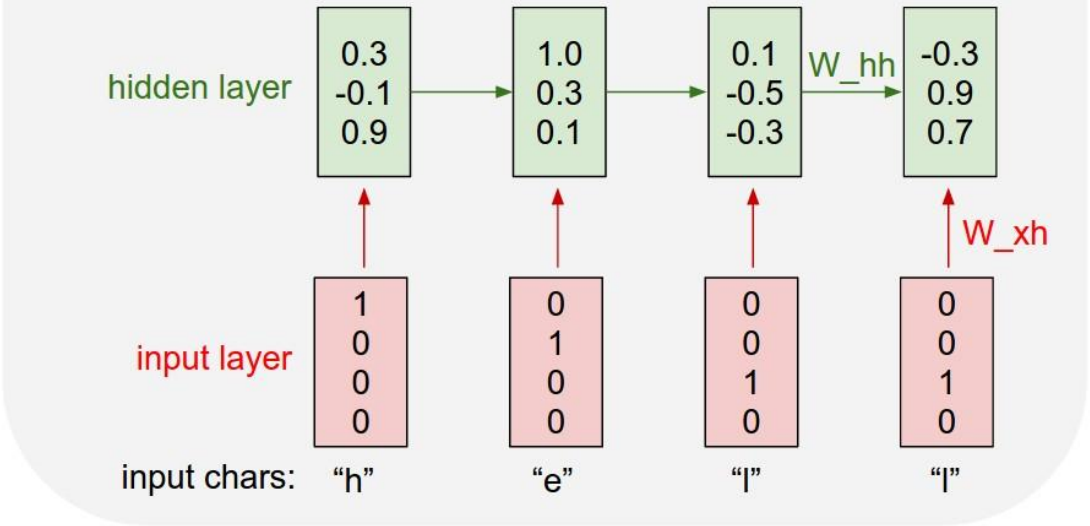

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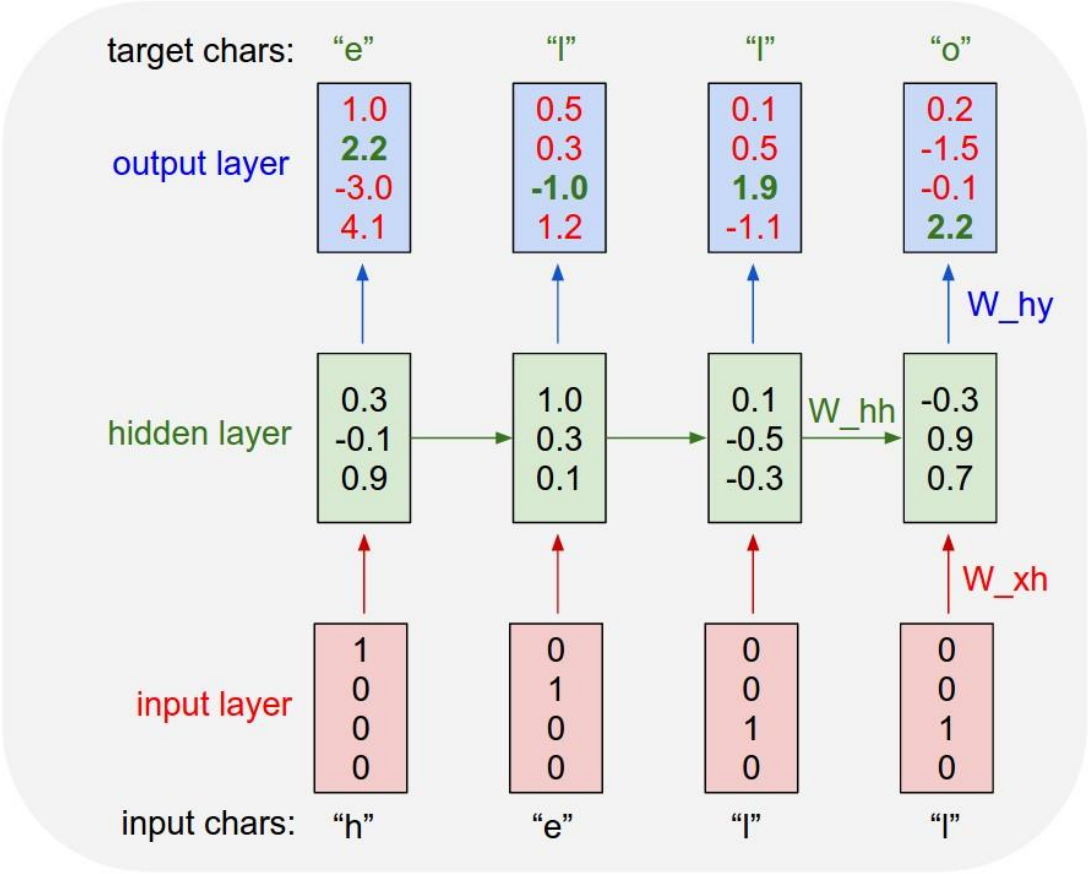

Example: Character-level Language Model Sampling

Vocabulary:
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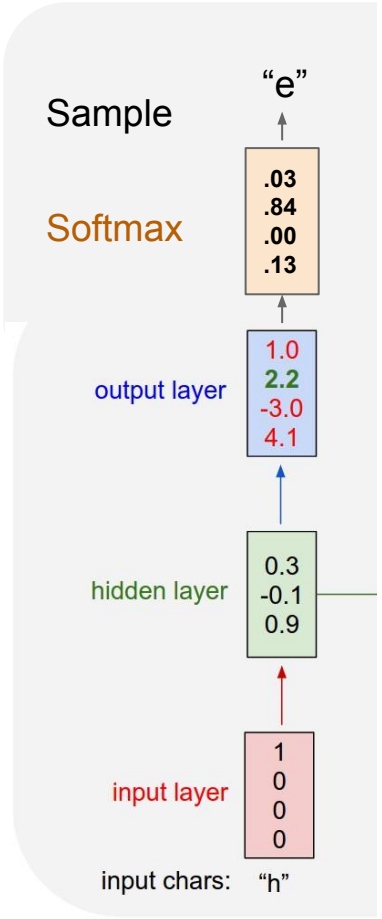
At test-time sample characters one at a time, feed back to model



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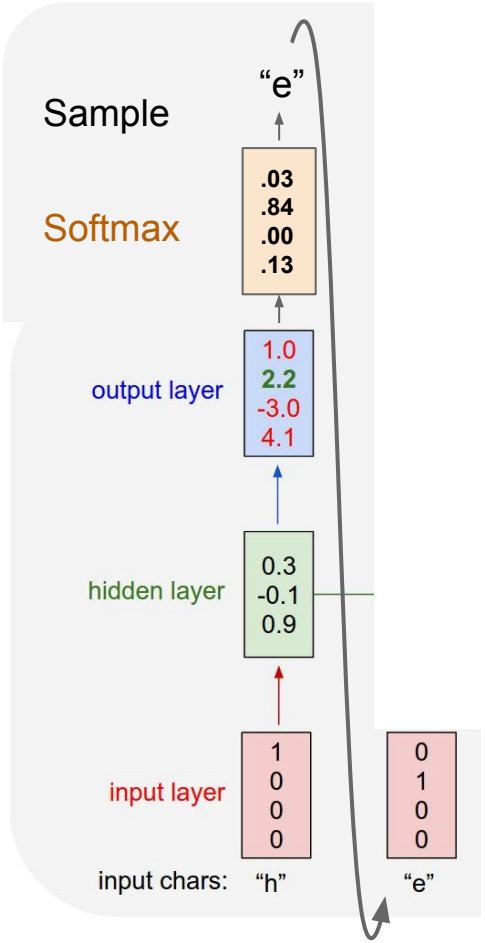

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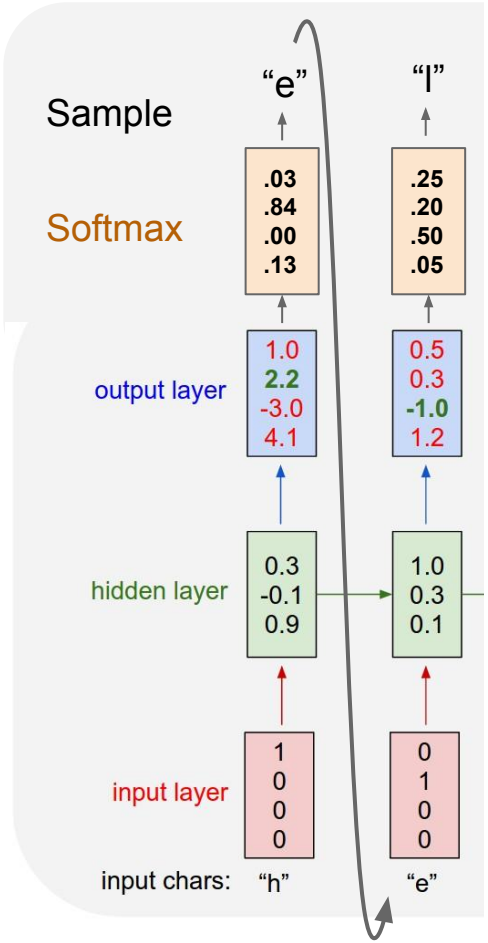

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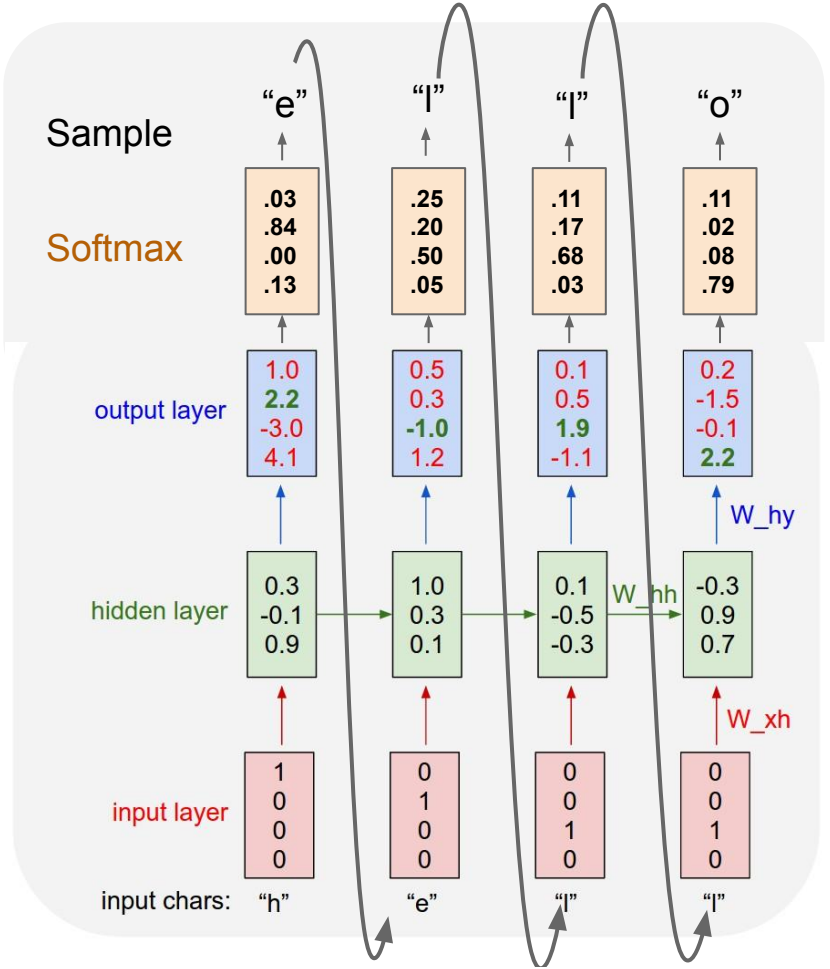
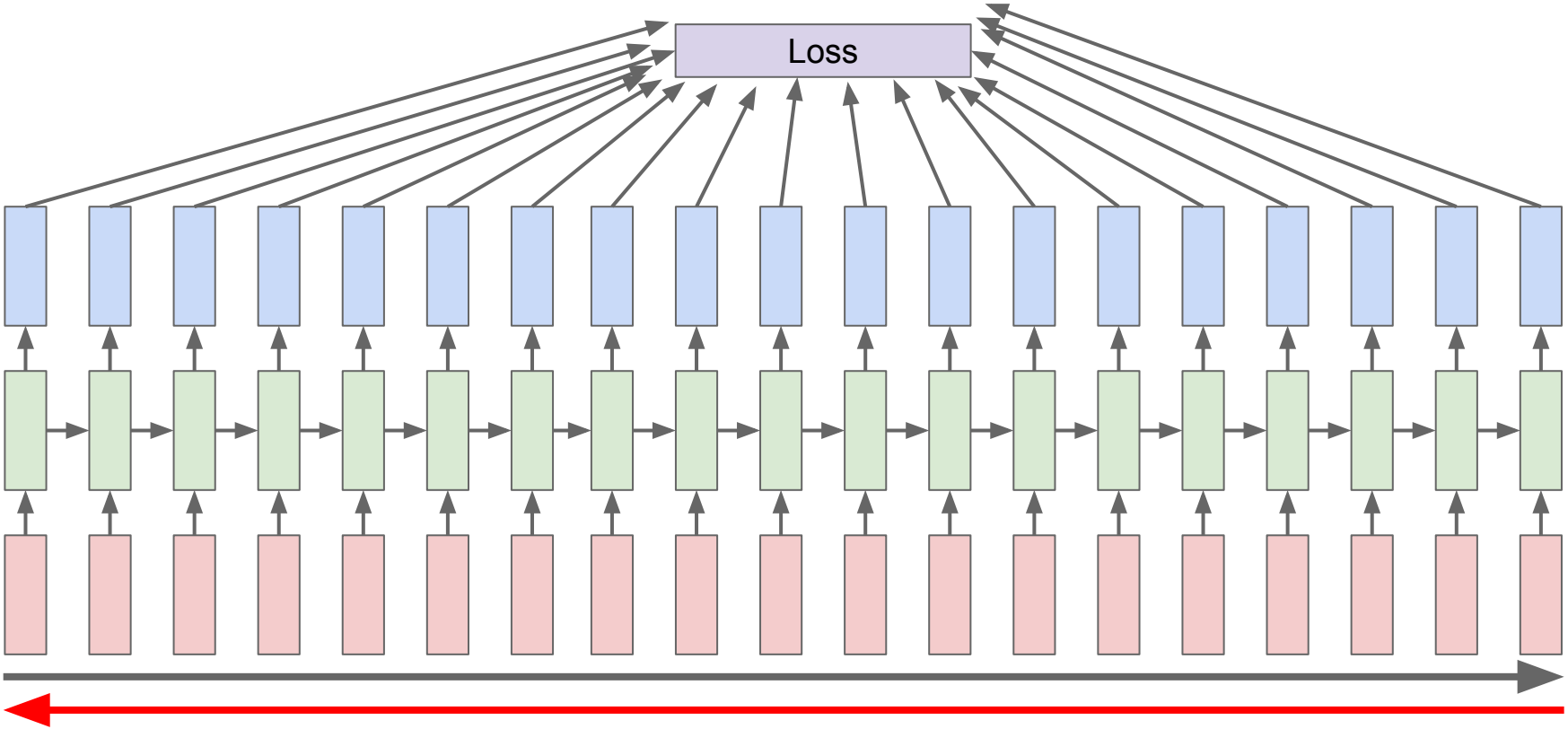
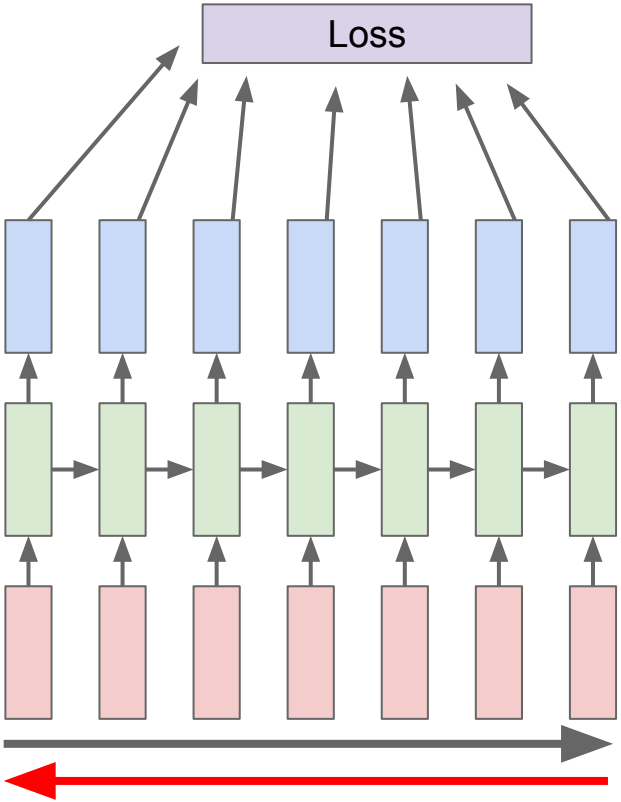


Backpropagation through time

Forward through entire sequence to compute loss, then backward through entire sequence to compute gradient

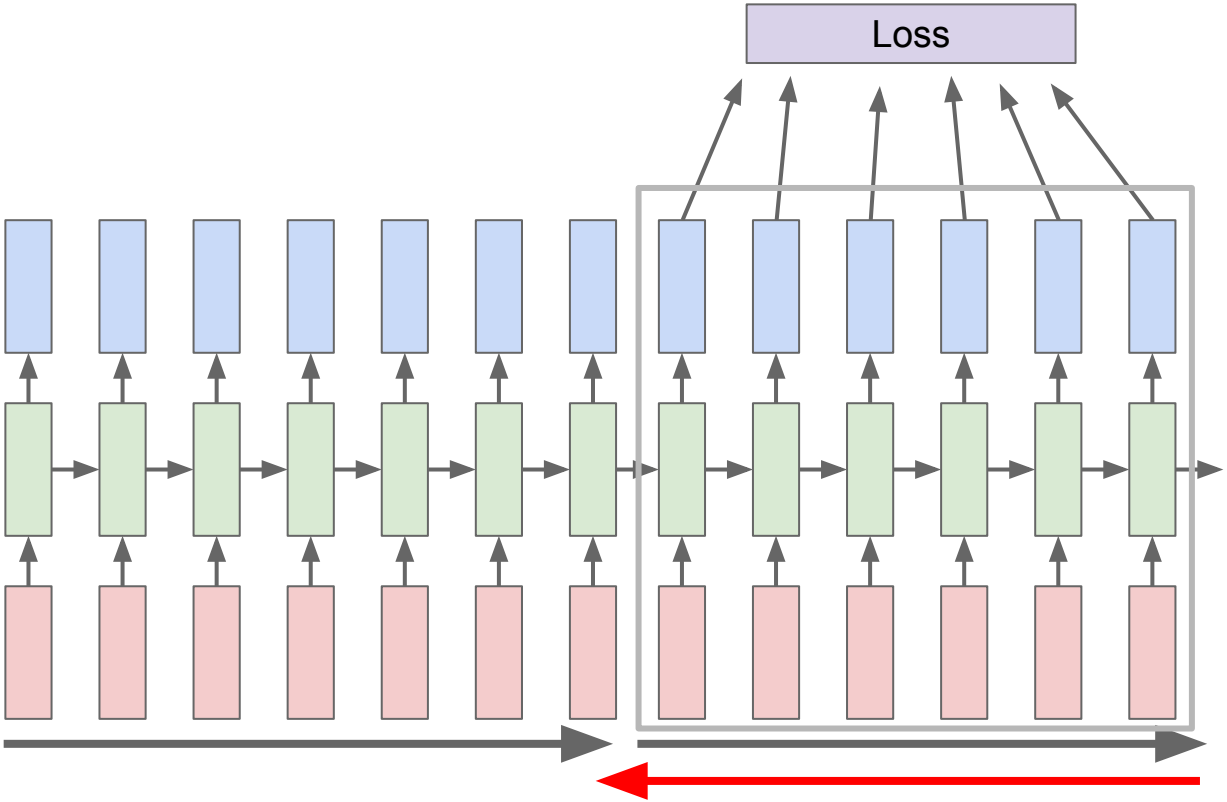


Truncated Backpropagation through time



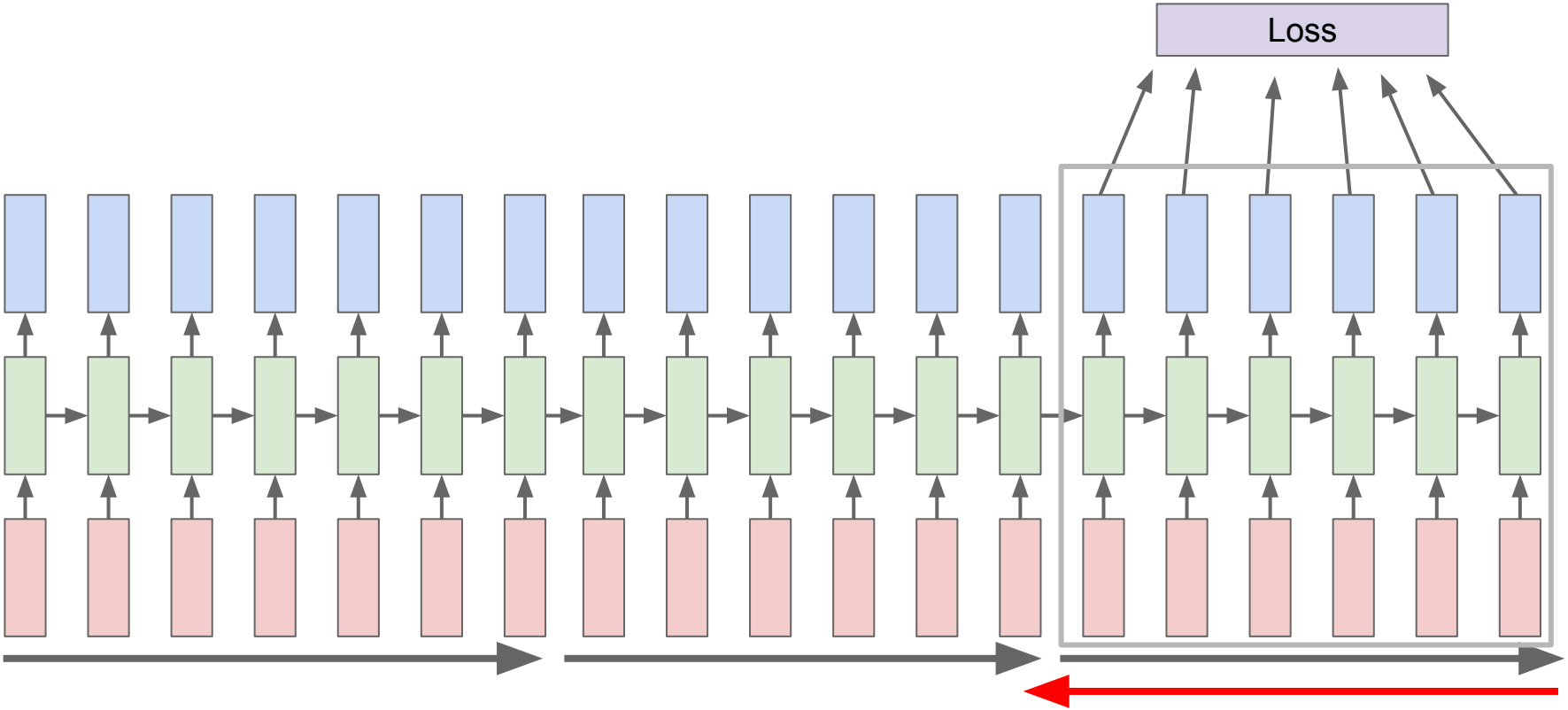
Run forward and backward through chunks of the sequence instead of whole sequence

Truncated Backpropagation through time



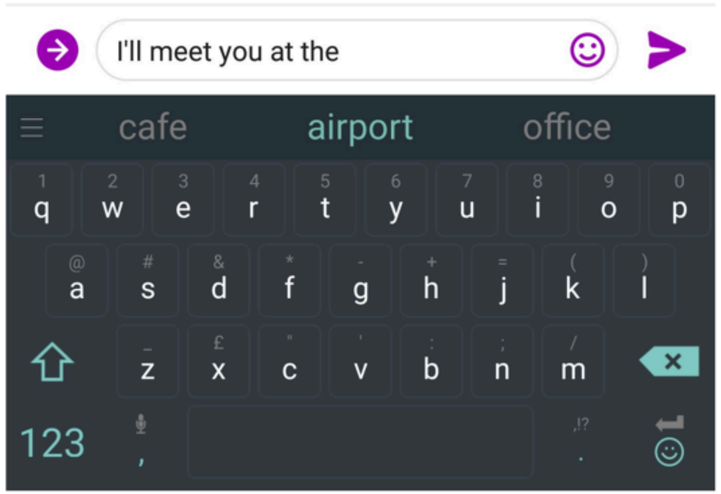
Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps

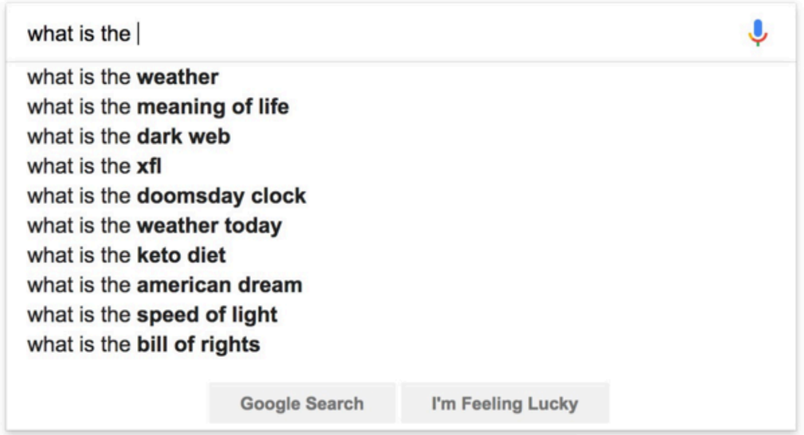
Truncated Backpropagation through time



Языковые модели (Language Models)

Задача: предсказать следующее слово по предыдущим





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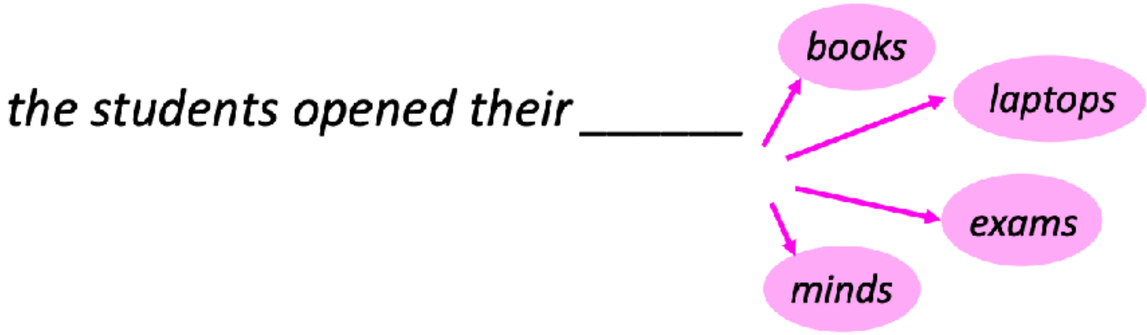
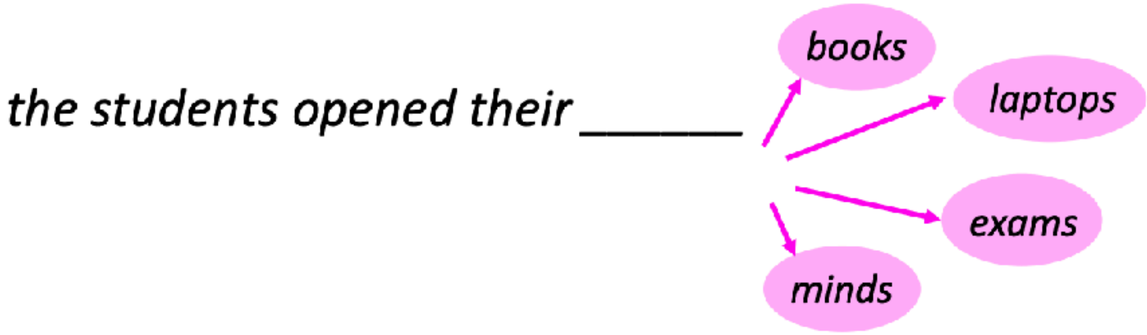


Авторегрессионная модель

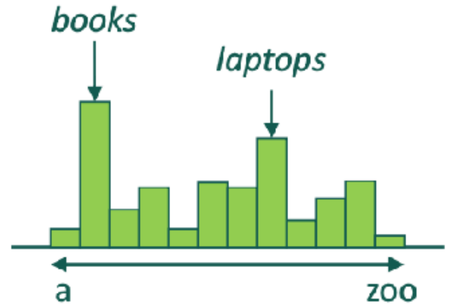
$$p(x) = p(x_n \mid x_1, \ldots, x_{n-1}) \cdot p(x_2 \mid x_1) \cdot p(x_1) = \prod_{i=1}^{n} p(x_i \mid x_1, \ldots, x_{i-1})$$

Языковые модели (Language Models)

Задача: предсказать следующее слово по предыдущим

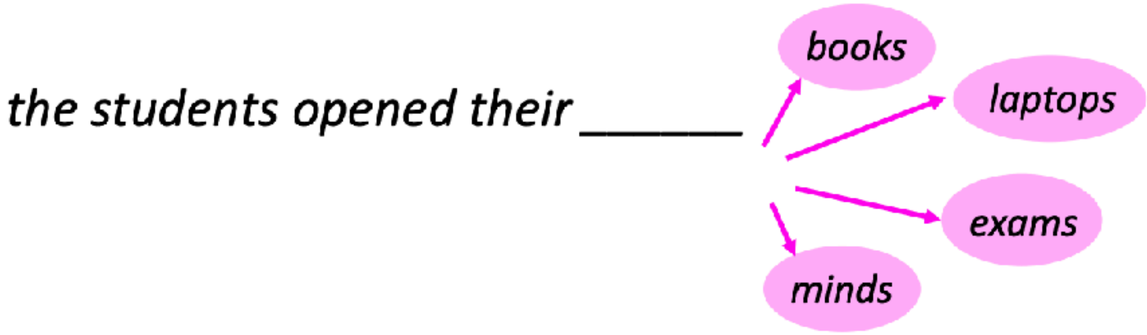


На выходе 5го шага: $p(x_5 \mid the, students, opened, their), x_5 \in Vocab$

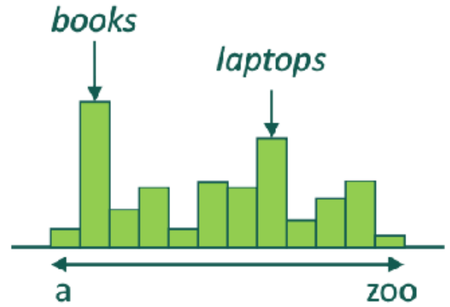


Языковые модели (Language Models)

Задача: предсказать следующее слово по предыдущим



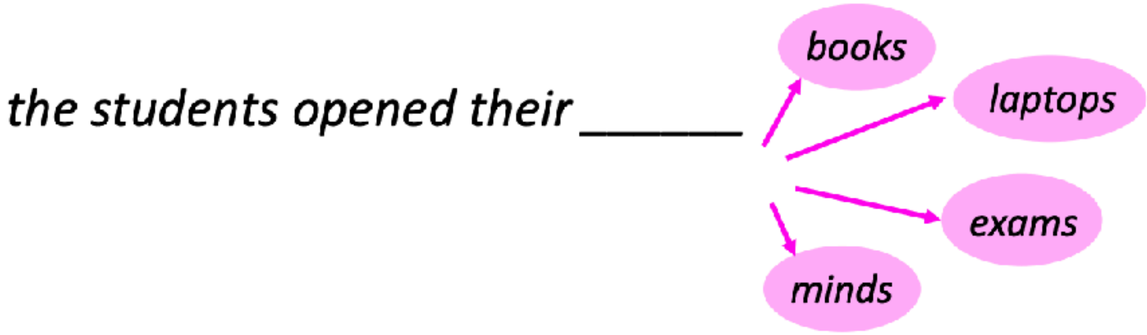
На выходе 5го шага: $p(x_5 \mid the, students, opened, their), x_5 \in Vocab$



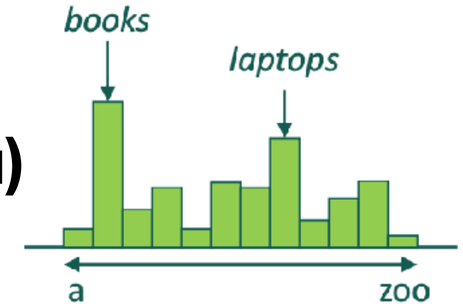
Классификация картинок: $p(class \mid image), class \in \{cat, dog, etc.\}$

Языковые модели (Language Models)

Задача: предсказать следующее слово по предыдущим



На выходе 5го шага: $p(x_5 \mid the, students, opened, their), x_5 \in Vocab$



Каждый шаг - классификация (выбираем слово из словаря)

Рекуррентные нейросети (RNN)

$p(x_5 \mid the, students, opened, their) = \textbf{Softmax}(\textbf{Linear}(h^t))$

h^t - представление (энкодинг) $the, students, opened, their$

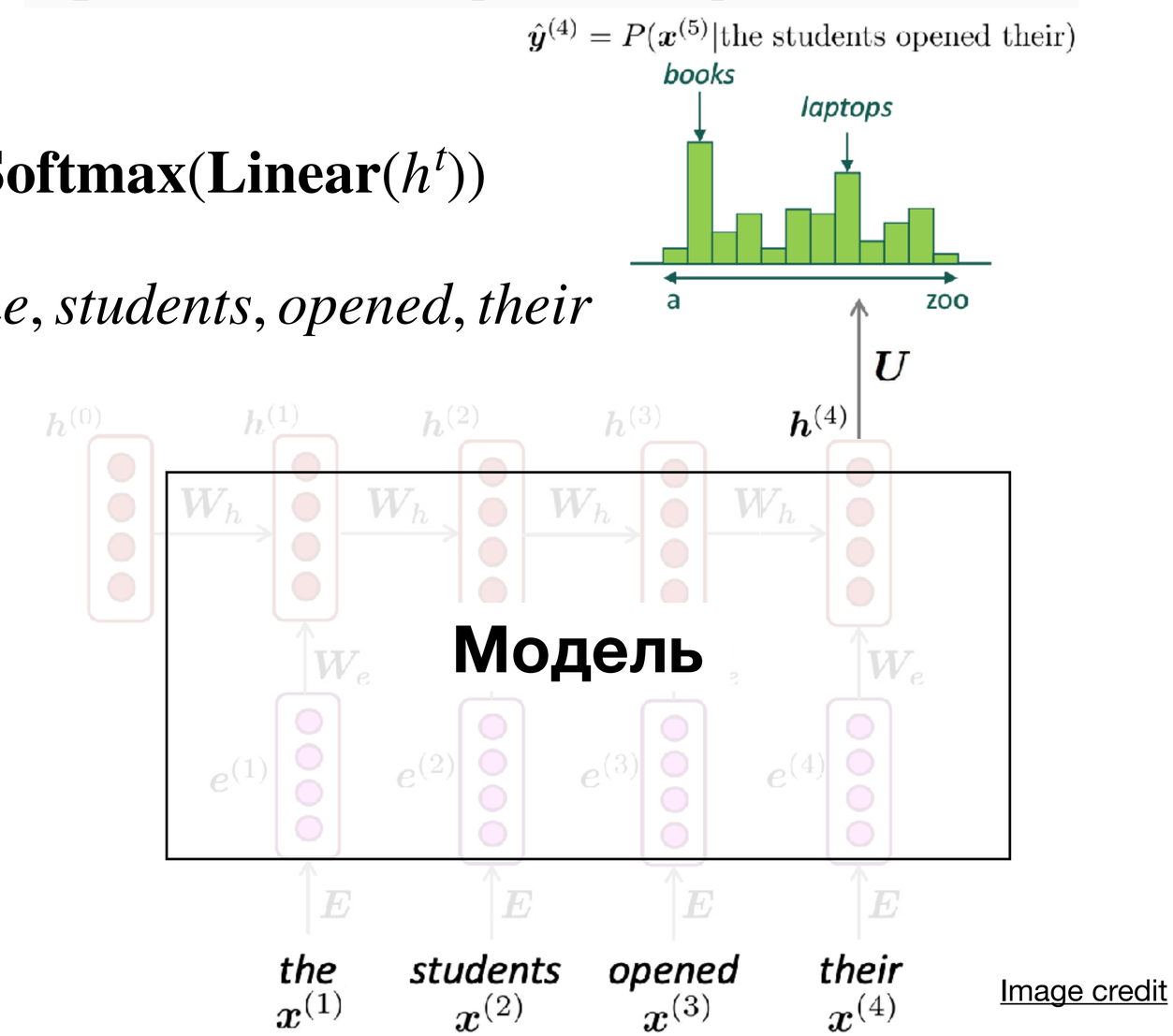


Image credit

Рекуррентные нейросети (RNN)

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h^t - представление (энкодинг) $the, students, opened, their$

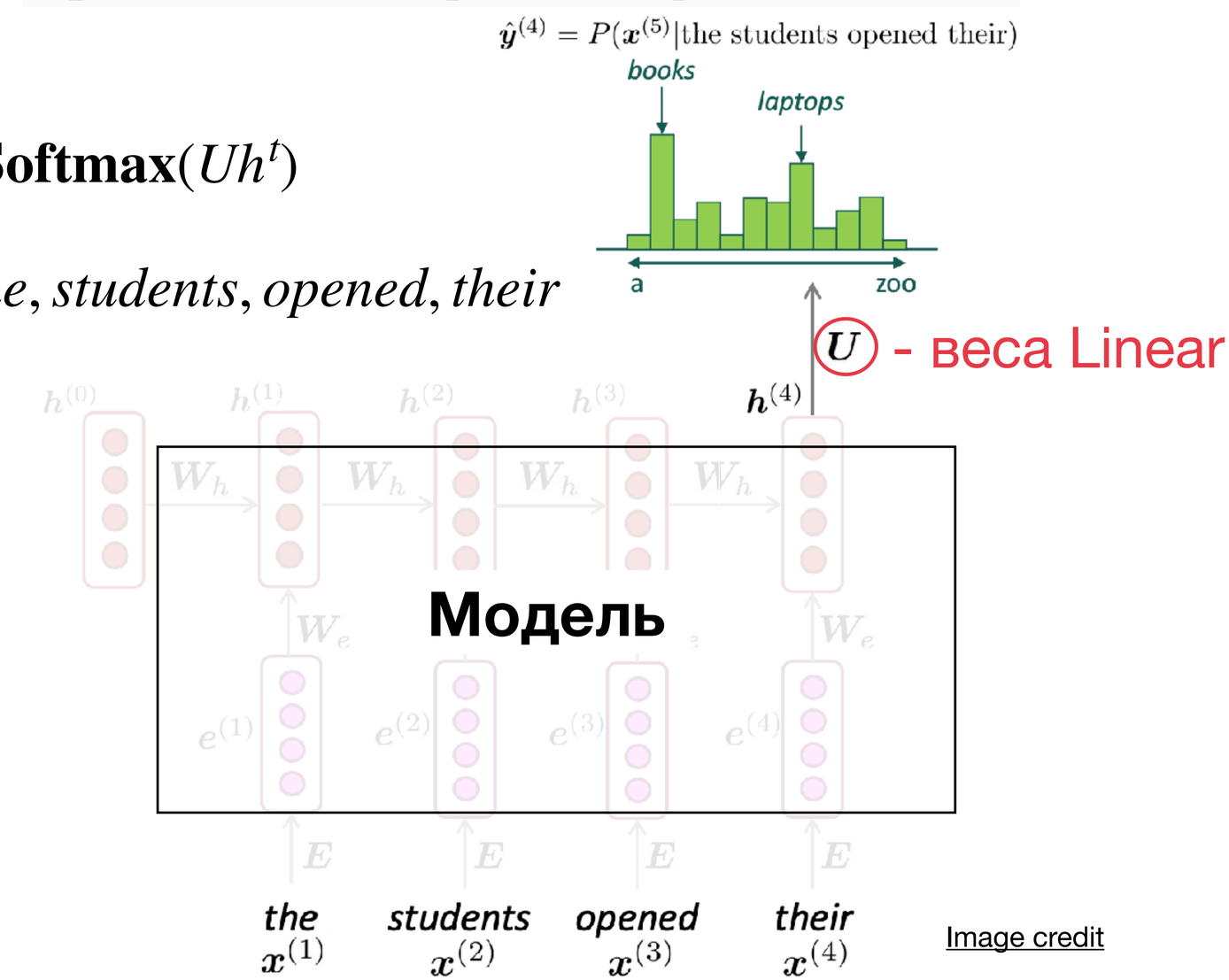

Image credit

Рекуррентные нейросети (RNN)

$p(x_5 \mid the, students, opened, their) = \mathbf{Softmax}(Uh^t)$

h^t - представление (энкодинг) $the, students, opened, their$

Как получить представления?

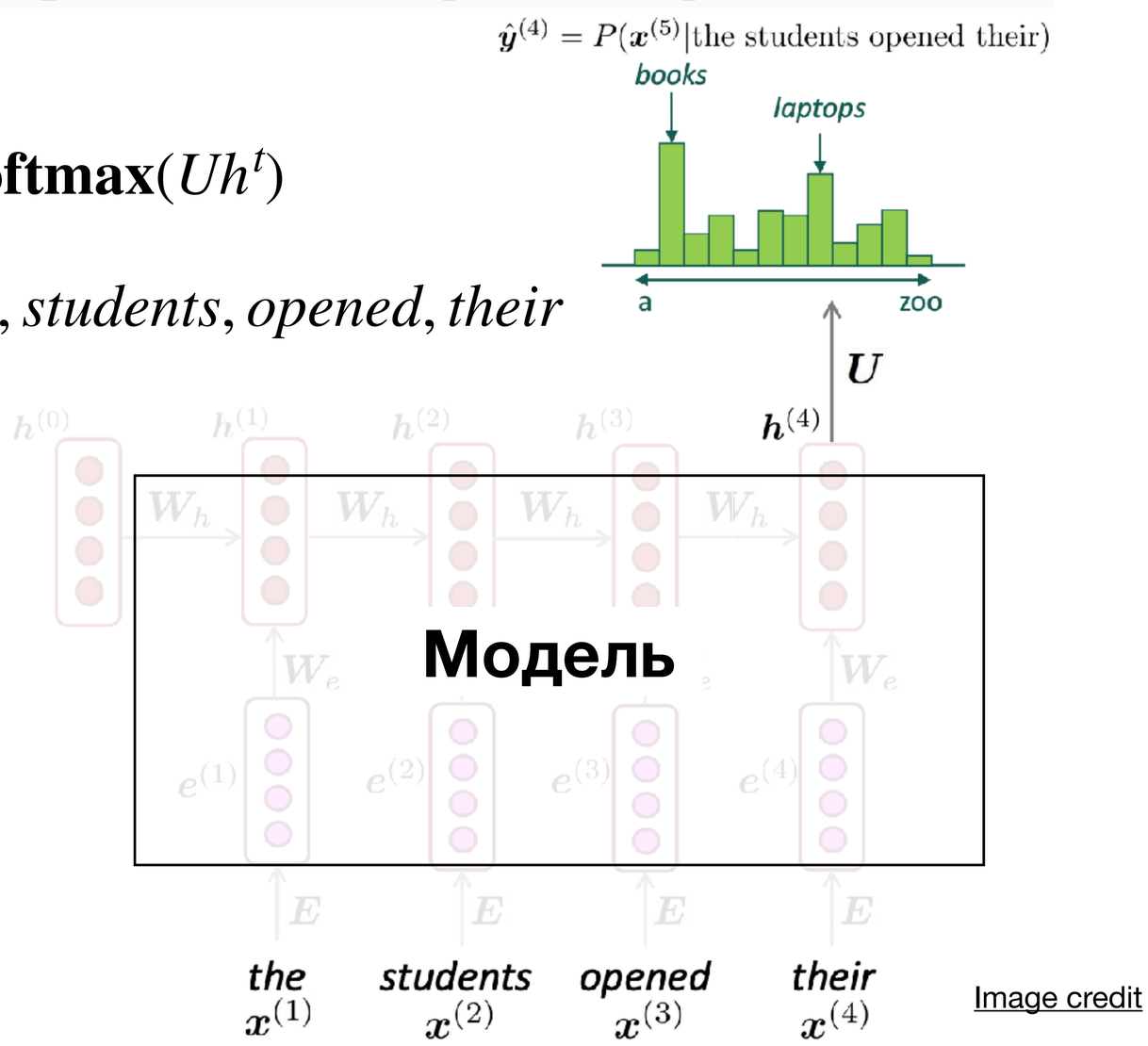

Image credit

Рекуррентные нейросети (RNN)

$$p(x_5 \mid the, students, opened, their) = \mathbf{Softmax}(Uh^t)$$

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Как получить представления?

Контекст (предыдущие слова) - может быть очень длинным!

Модель должна уметь обрабатывать и 1, и 100 слов

"As he crossed toward the pharmacy at the corner he involuntarily turned his head because of a burst of light that had ricocheted from his temple, and saw, with that quick smile with which we greet a rainbow or a rose, a blindingly white parallelogram of sky being unloaded from the van —a dresser with mirrors across which, as across a cinema screen, passed a flawlessly clear reflection of boughs sliding and swaying not arboreally, but with a human vacillation, produced by the nature of those who were carrying this sky, these boughs, this gliding façade."

Рекуррентные нейросети (RNN)

$p(x_5 \mid the, students, opened, their) = \mathbf{Softmax}(Uh^t)$

h^t - представление (энкодинг) $the, students, opened, their$

Как получить представления?

Контекст (предыдущие слова) - может быть очень длинным!

Модель должна уметь обрабатывать и 1, и 100 слов

Идея: будем сохранять историю в “кэше” (специальный вектор, ***hidden state***)

Рекуррентные нейросети (RNN)

Шаг 0: инициализируем “кэш” - $h^0 = 0$

Рекуррентные нейросети (RNN)

Шаг 1: пусть первое слово известно - *the*

Хотим предсказать второе - *students*

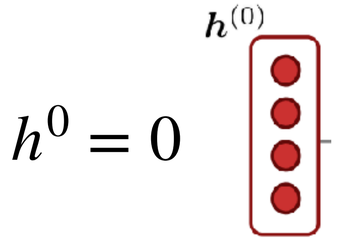


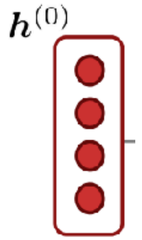
Image credit

Рекуррентные нейросети (RNN)

Шаг 1: пусть первое слово известно - *the*

Хотим предсказать второе - *students*

$h^0 = 0$



Возьмем эмбеддинг word2vec e^1 для *the*

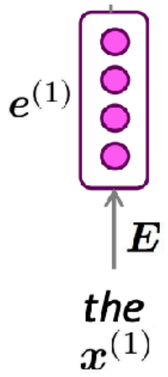


Image credit

Рекуррентные нейросети (RNN)

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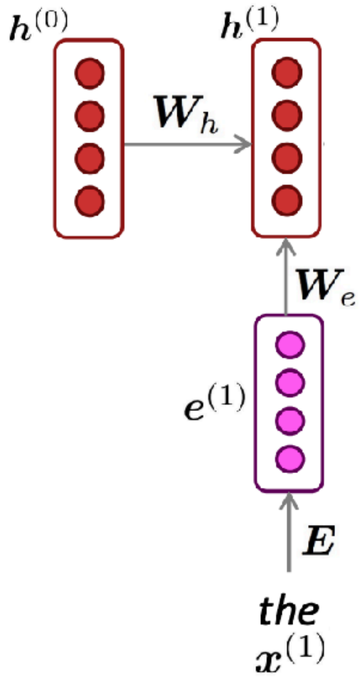
Хотим предсказать второе - *students*

$h^0 = 0$



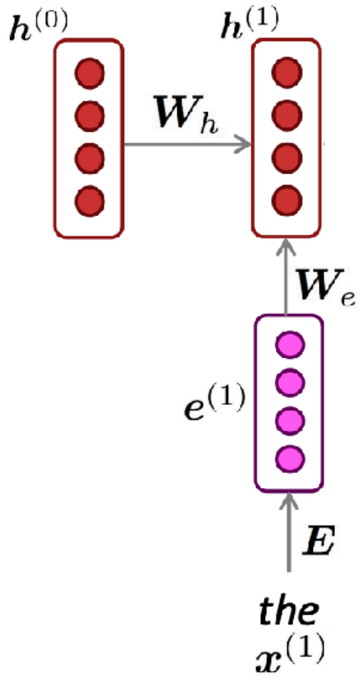
$h^1 = Sigmoid(Linear(h^0) + Linear(e^1))$

Image credit

Рекуррентные нейросети (RNN)

Шаг 1: пусть первое слово известно - *the*

Хотим предсказать второе - *students*



$h^0 = 0$

$h^1 = Sigmoid(Linear(h^0) + Linear(e^1))$

- веса W_h

- веса W_e

Image credit

Рекуррентные нейросети (RNN)

Шаг 1: пусть первое слово известно - *the*

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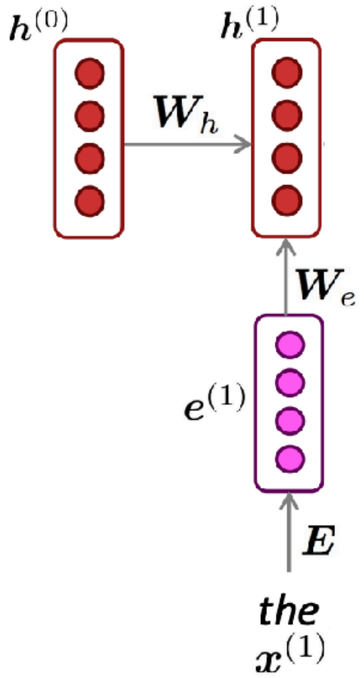


$h^1 = Sigmoid(Linear(h^0) + Linear(e^1))$

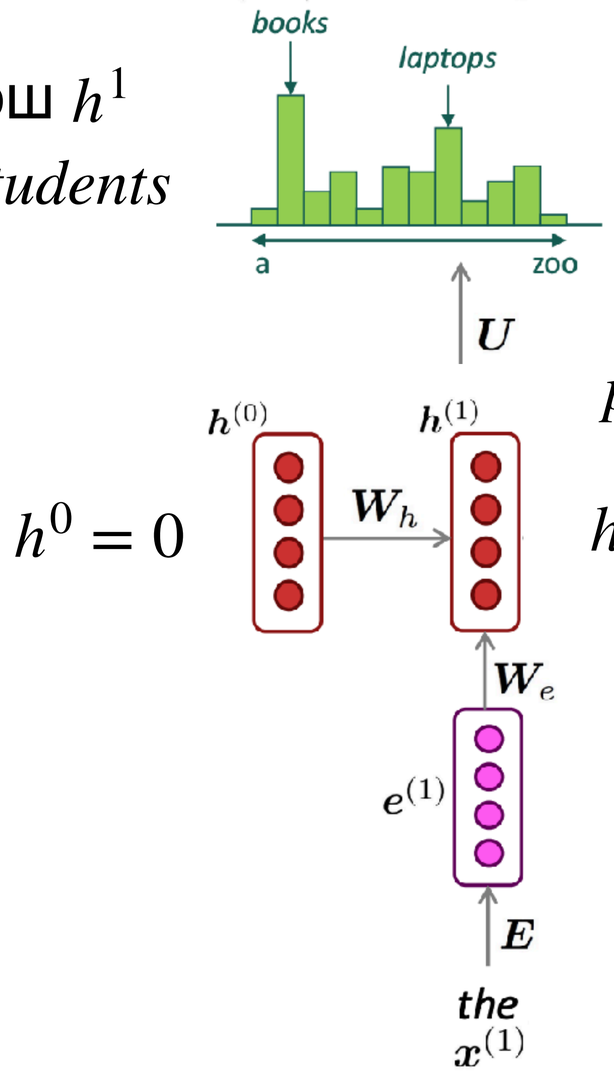
“история” текущее слово

Image credit

Рекуррентные нейросети (RNN)

Шаг 1: пересчитываем кэш h^1

предсказываем *students*



$$h^0 = 0$$

$$p(x_2 \mid the) = Softmax(Linear(h^1))$$

$$h^1 = Sigmoid(Linear(h^0) + Linear(e^1))$$

новая “история”

информация про the

Image credit

Рекуррентные нейросети (RNN)

Шаг 2: есть h^1 (информация про *the*)

текущее слово - *students*

хотим предсказать *opened*

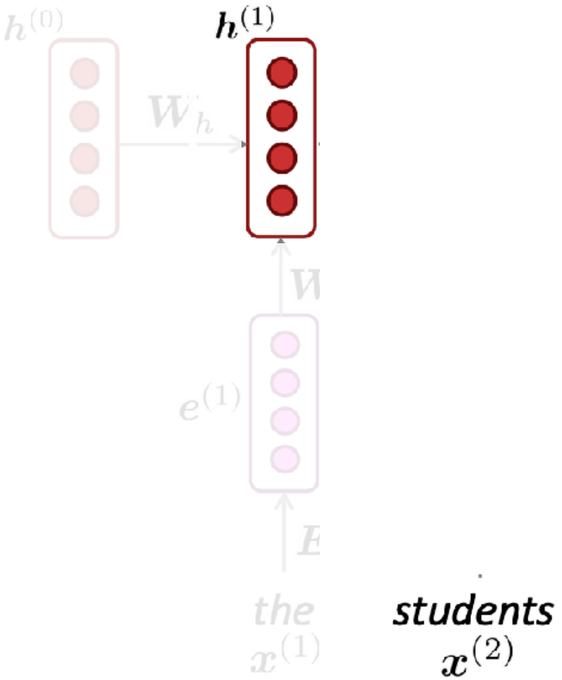


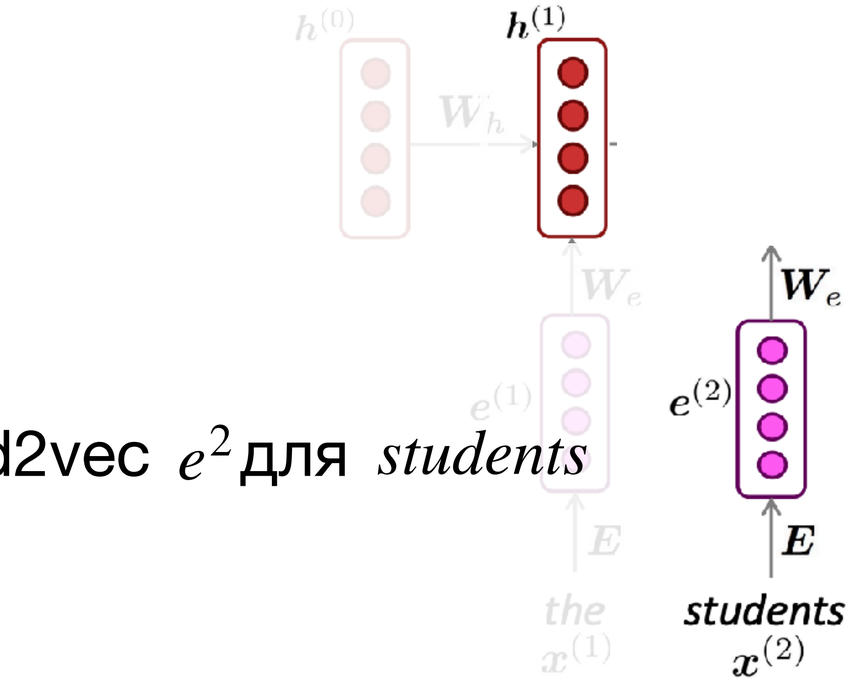
Image credit

Рекуррентные нейросети (RNN)

Шаг 2: есть h^1 (информация про the)

текущее слово - $students$

хотим предсказать $opened$



Возьмем эмбеддинг word2vec e^2 для $students$

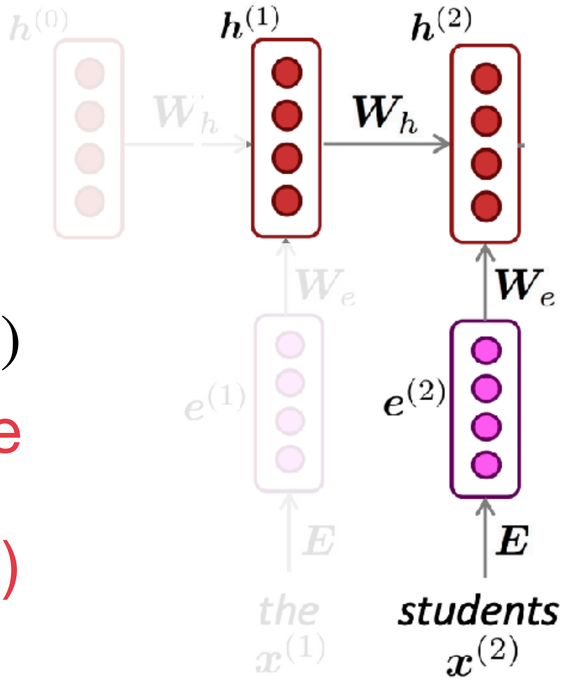
Image credit

Рекуррентные нейросети (RNN)

Шаг 2: есть h^1 (информация про *the*)

текущее слово - *students*

хотим предсказать *opened*



$$h^2 = Sigmoid(Linear(h^1) + Linear(e^2))$$

“история” (*the*)

текущее слово (*students*)

Image credit

Рекуррентные нейросети (RNN)

Шаг 2: есть h^1 (информация про *the*)

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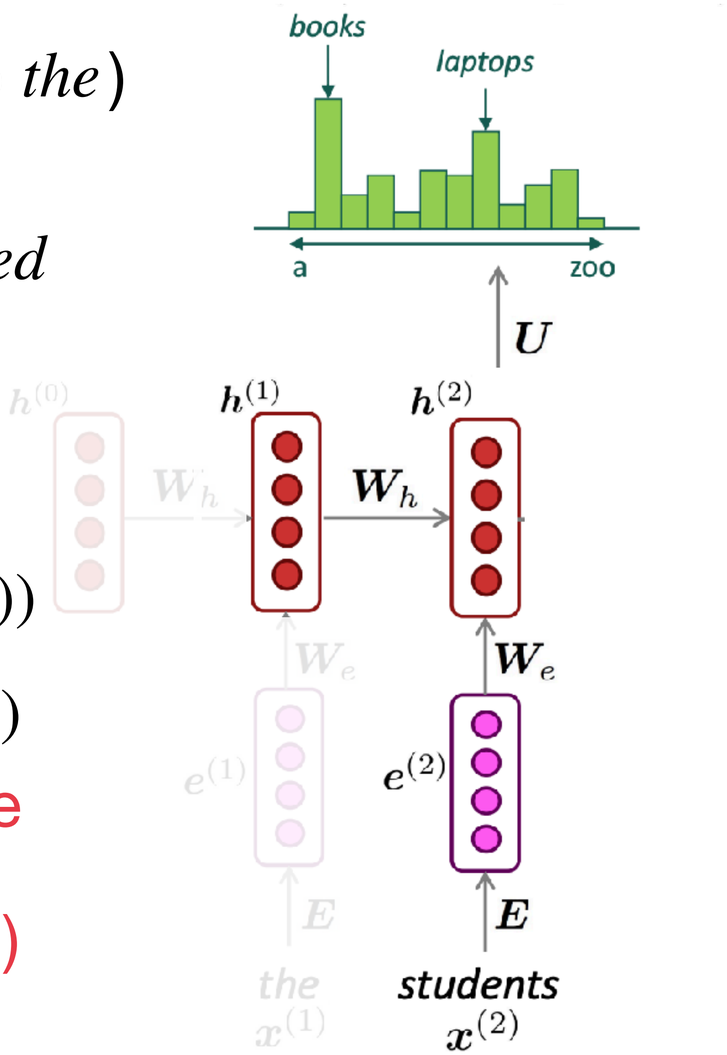
хотим предсказать *opened*



$$p(x_3 \mid the, students) = Softmax(Linear(h^2))$$

$$h^2 = Sigmoid(Linear(h^1) + Linear(e^2))$$

“история” (*the*)

текущее слово (*students*)

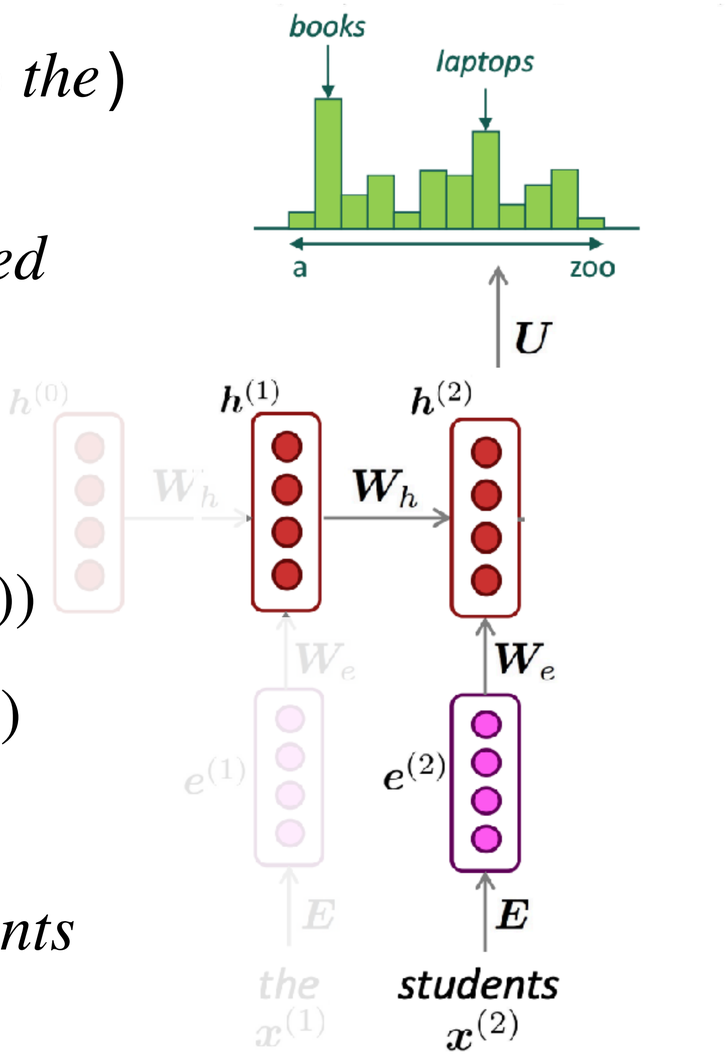
Image credit

Рекуррентные нейросети (RNN)

Шаг 2: есть h^1 (информация про *the*)

текущее слово - *students*

хотим предсказать *opened*



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$$h^2 = Sigmoid(Linear(h^1) + Linear(e^2))$$

новая “история”

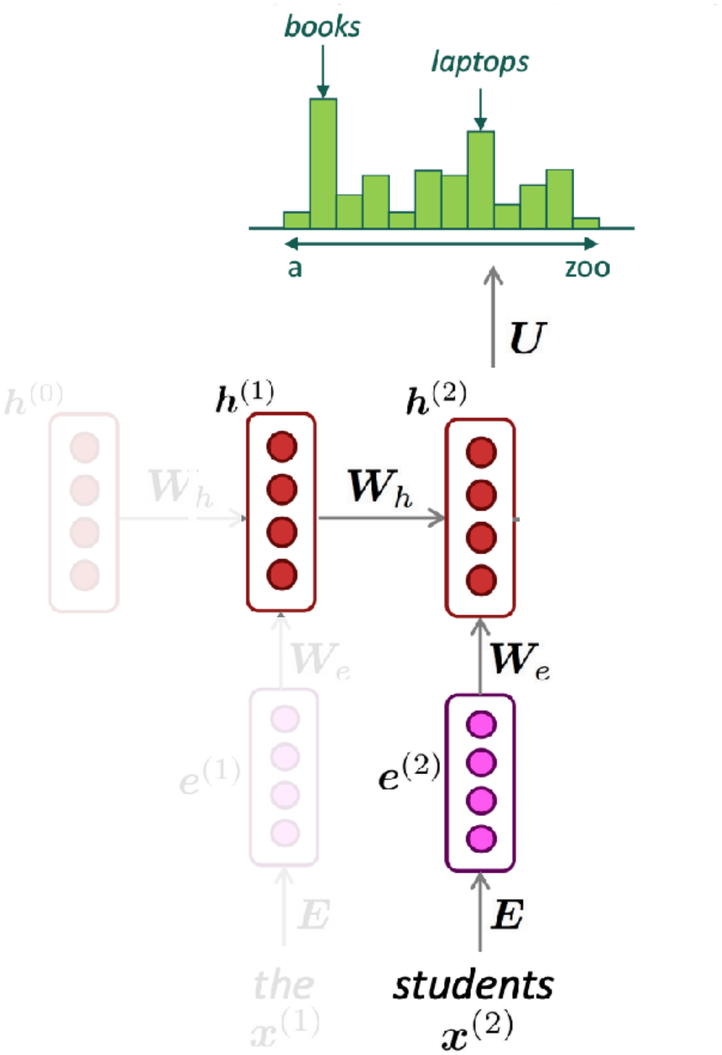
информация про the (h^1), *students*

Image credit

Рекуррентные нейросети (RNN)

Шаг 2: пересчитываем кэш h^2

предсказываем *opened*



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Рекуррентные нейросети (RNN)

Два шага RNN

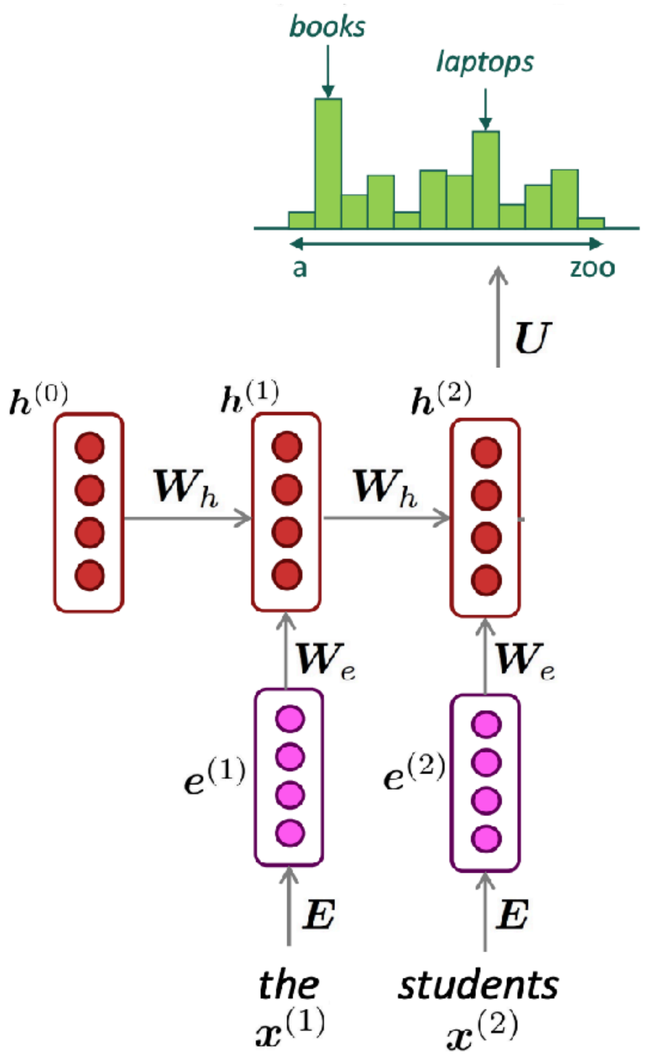

Image credit

Рекуррентные нейросети (RNN)

output distribution

$$\hat{\boldsymbol{y}}^{(t)} = \text{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$$

hidden states

$$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$$

$\boldsymbol{h}^{(0)}$ is the initial hidden state

word embeddings

$$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)}$$

words / one-hot vectors

$$\boldsymbol{x}^{(t)} \in \mathbb{R}^{|V|}$$

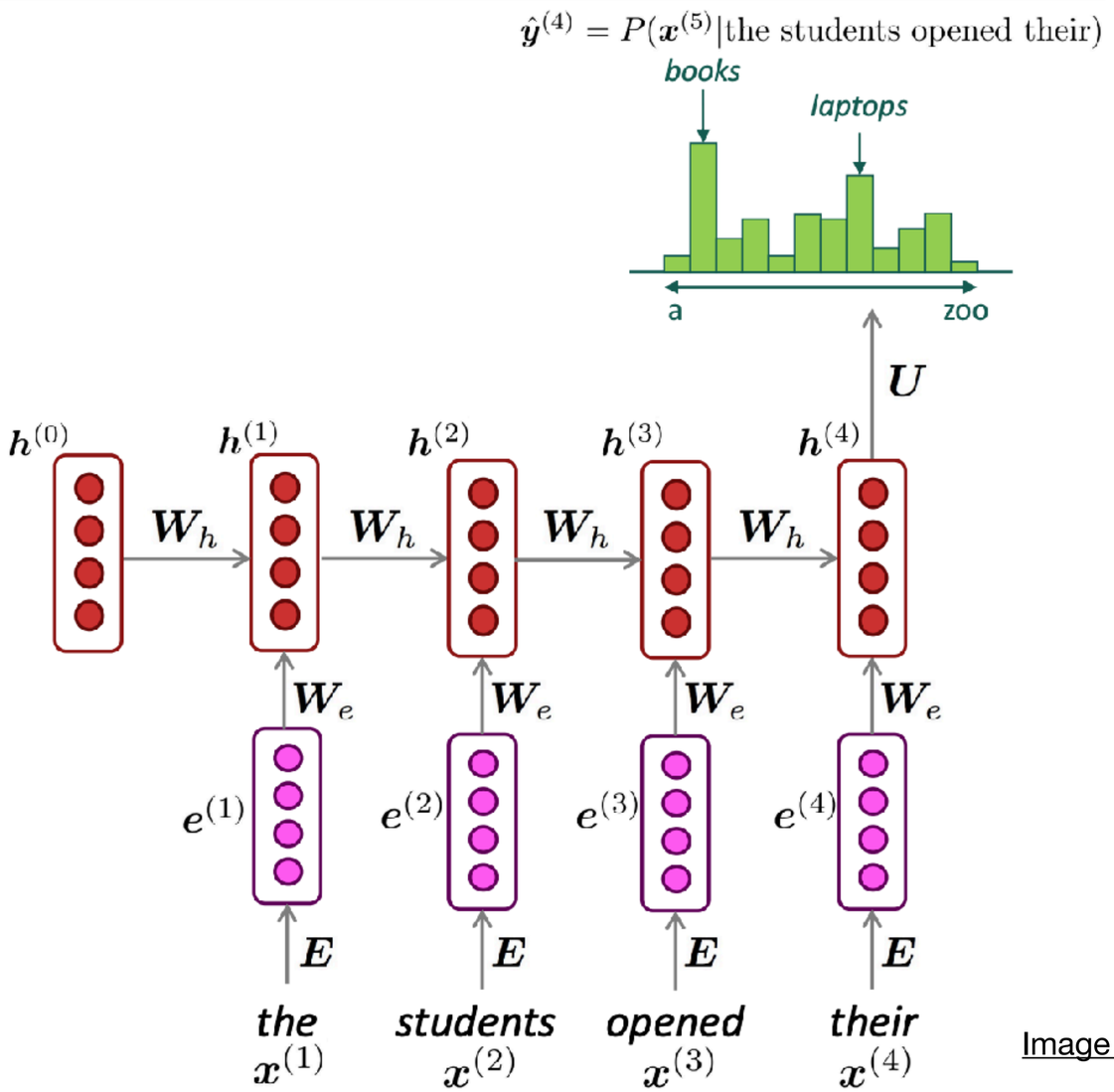

Image credit

Рекуррентные нейросети (RNN)

Обучение: лосс для классификации на каждом шаге

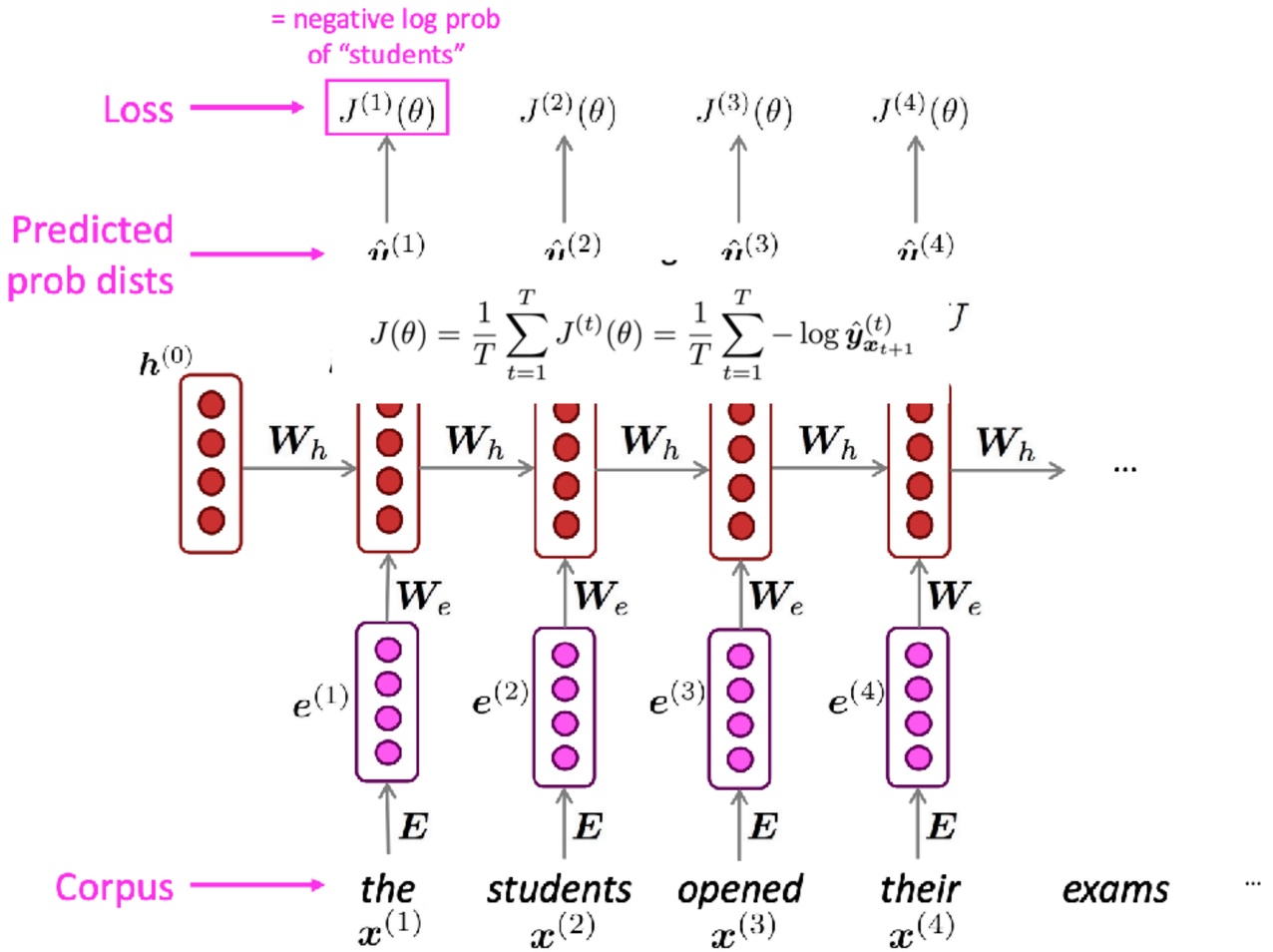

Image credit

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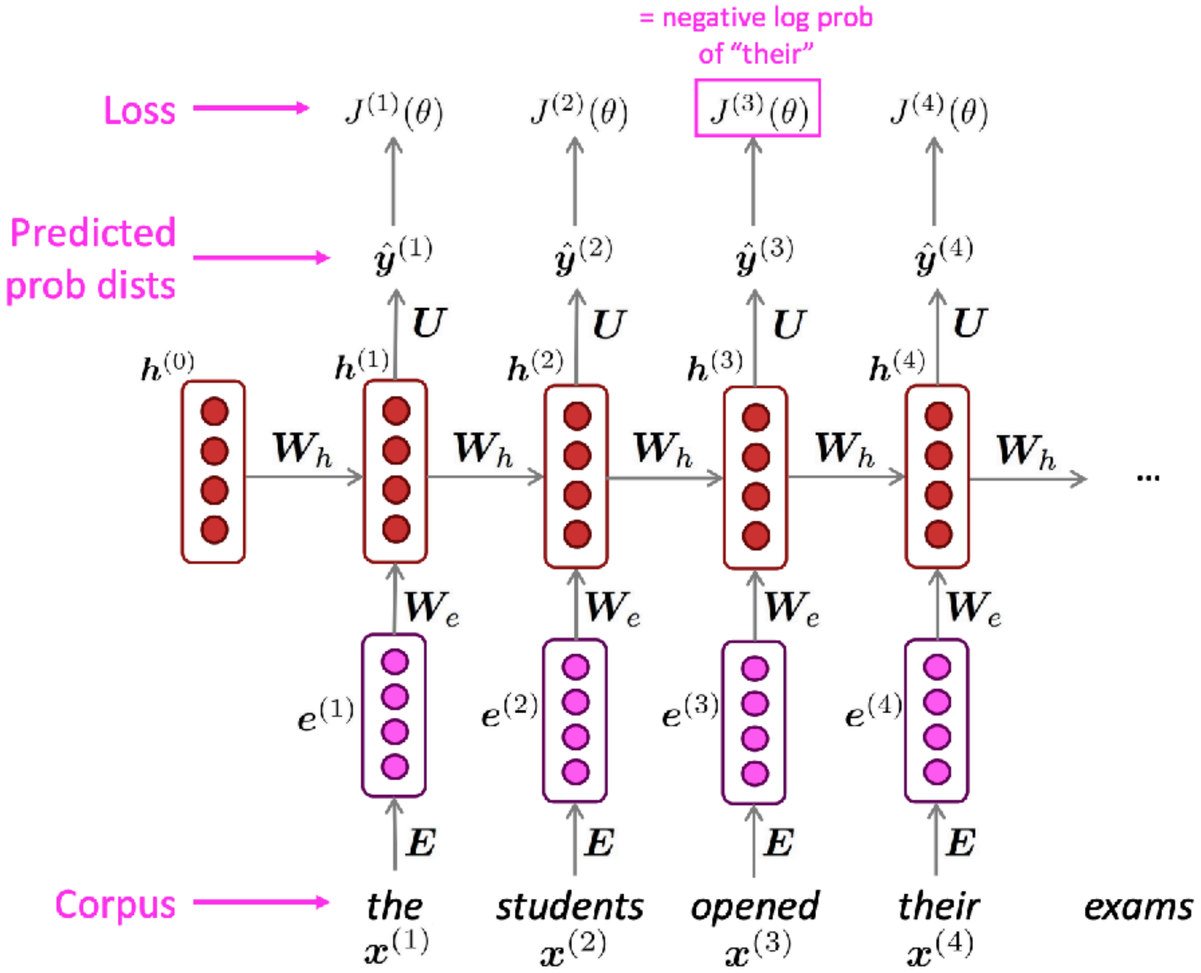

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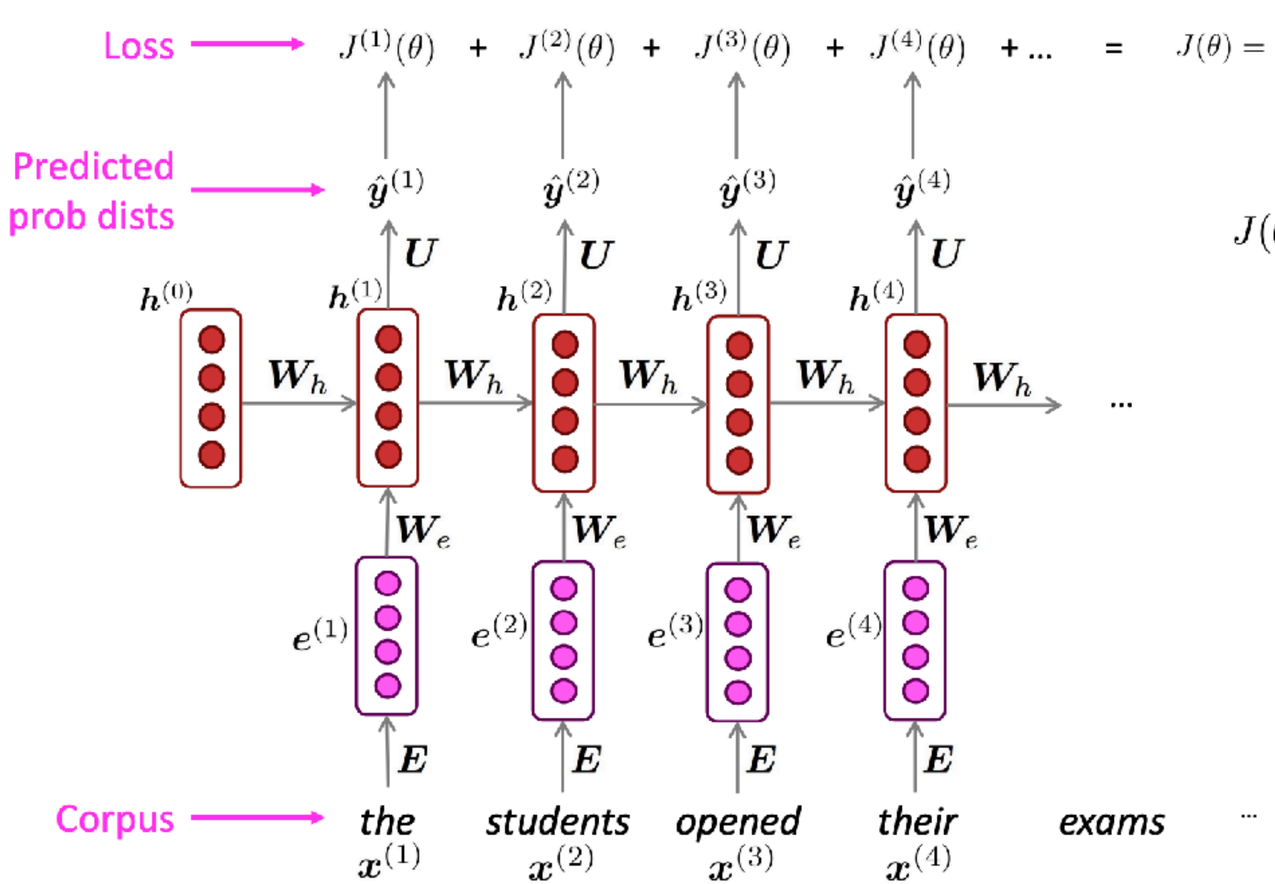
Обучение: лосс для классификации на каждом шаге

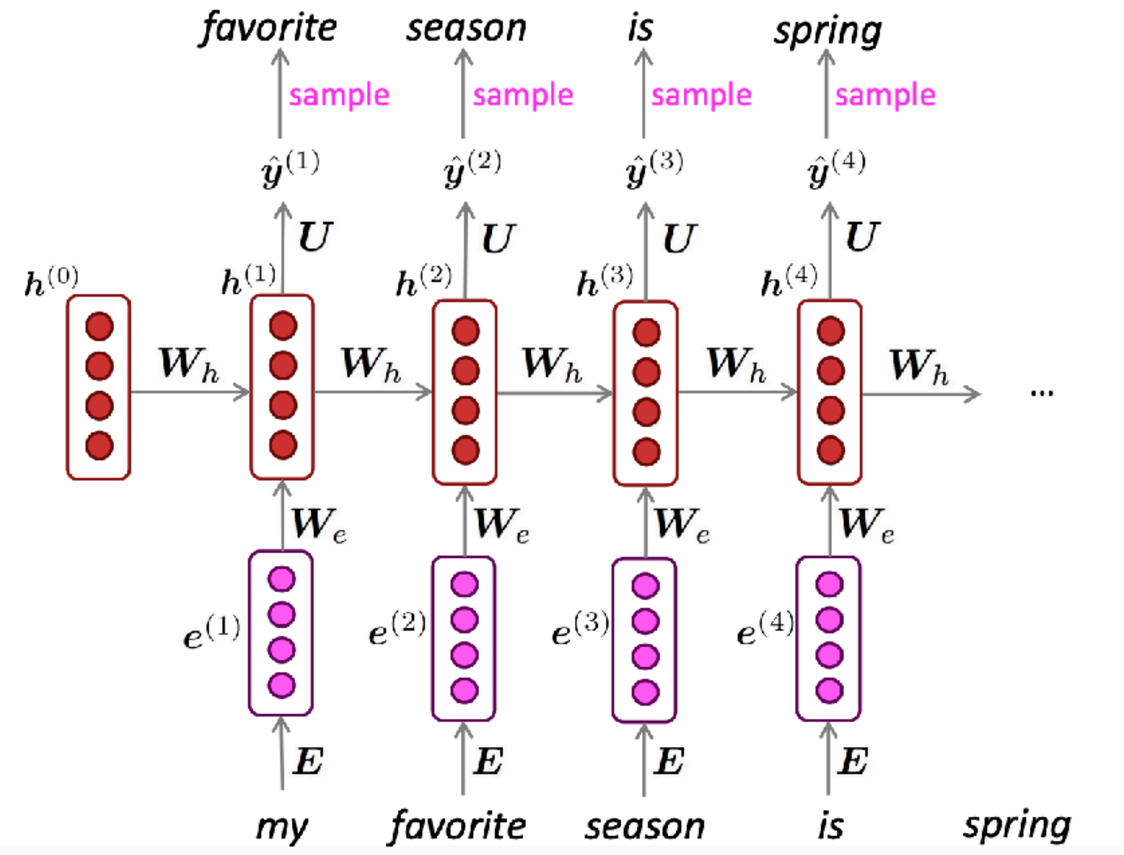


$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} J^{(t)}(\theta) = \frac{1}{T}\sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}}$$

Image credit

Рекуррентные нейросети (RNN)

Генерация текста (language modeling)



"Sorry," Harry shouted, panicking—"I'll leave those brooms in London, are they?"

"No idea," said Nearly Headless Nick, casting low close by Cedric, carrying the last bit of treacle Charms, from Harry's shoulder, and to answer him the common room perched upon it, four arms held a shining knob from when the spider hadn't felt it seemed. He reached the teams too.

Image credit

Рекуррентные нейросети (RNN)

Можно использовать для других задач!

output distribution

$$\hat{\boldsymbol{y}}^{(t)} = \text{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$$

hidden states

$$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$$

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word embeddings

$$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)}$$

words / one-hot vectors

$$\boldsymbol{x}^{(t)} \in \mathbb{R}^{|V|}$$

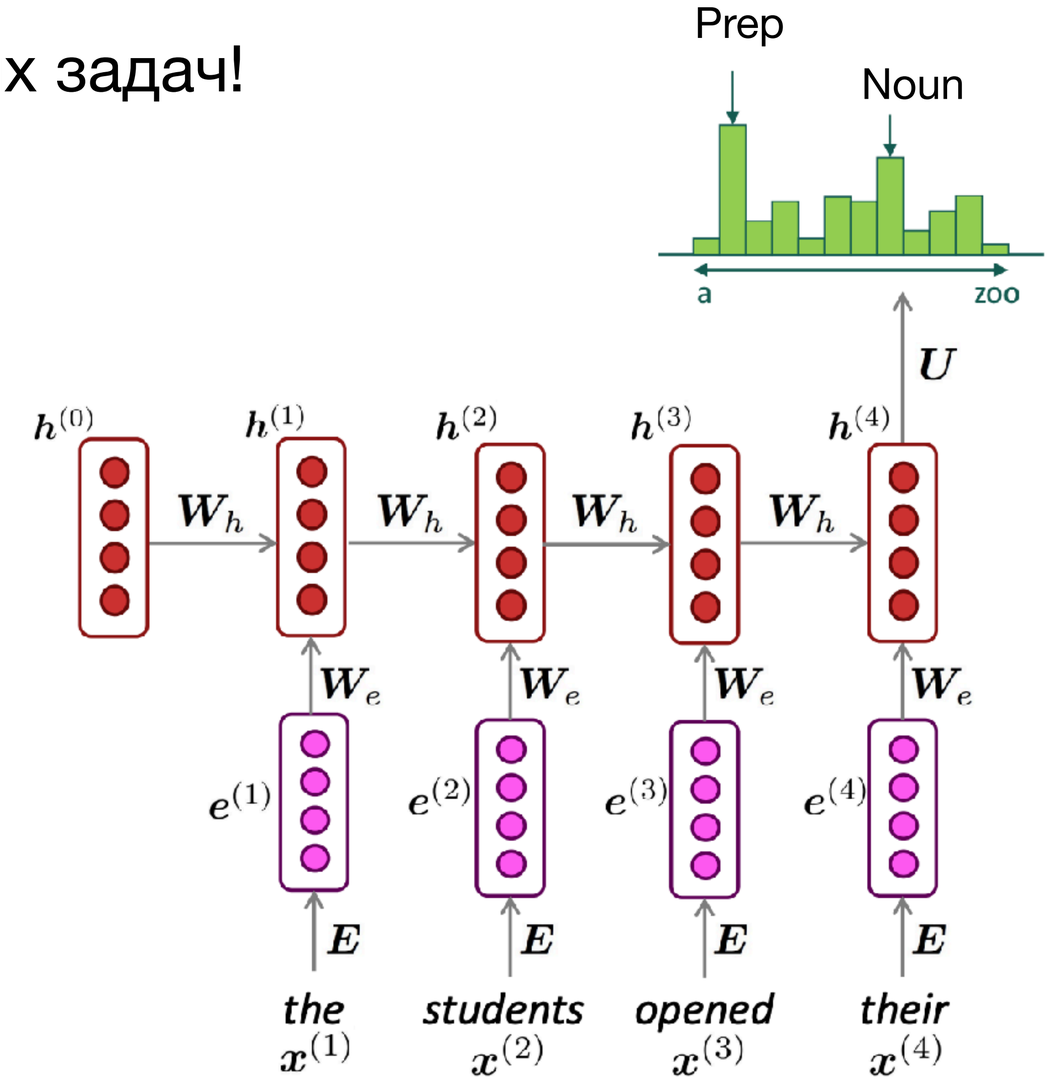


Image credit

Рекуррентные нейросети (RNN)

Можно использовать для других задач!

Sentence classification

Классификация предложений — это задача в области обработки естественного языка (NLP), заключающаяся в определении категории или метки для данного предложения. Это может быть полезно в различных приложениях, таких как анализ тональности, фильтрация спама, автоматическая категоризация текстов и многое другое.

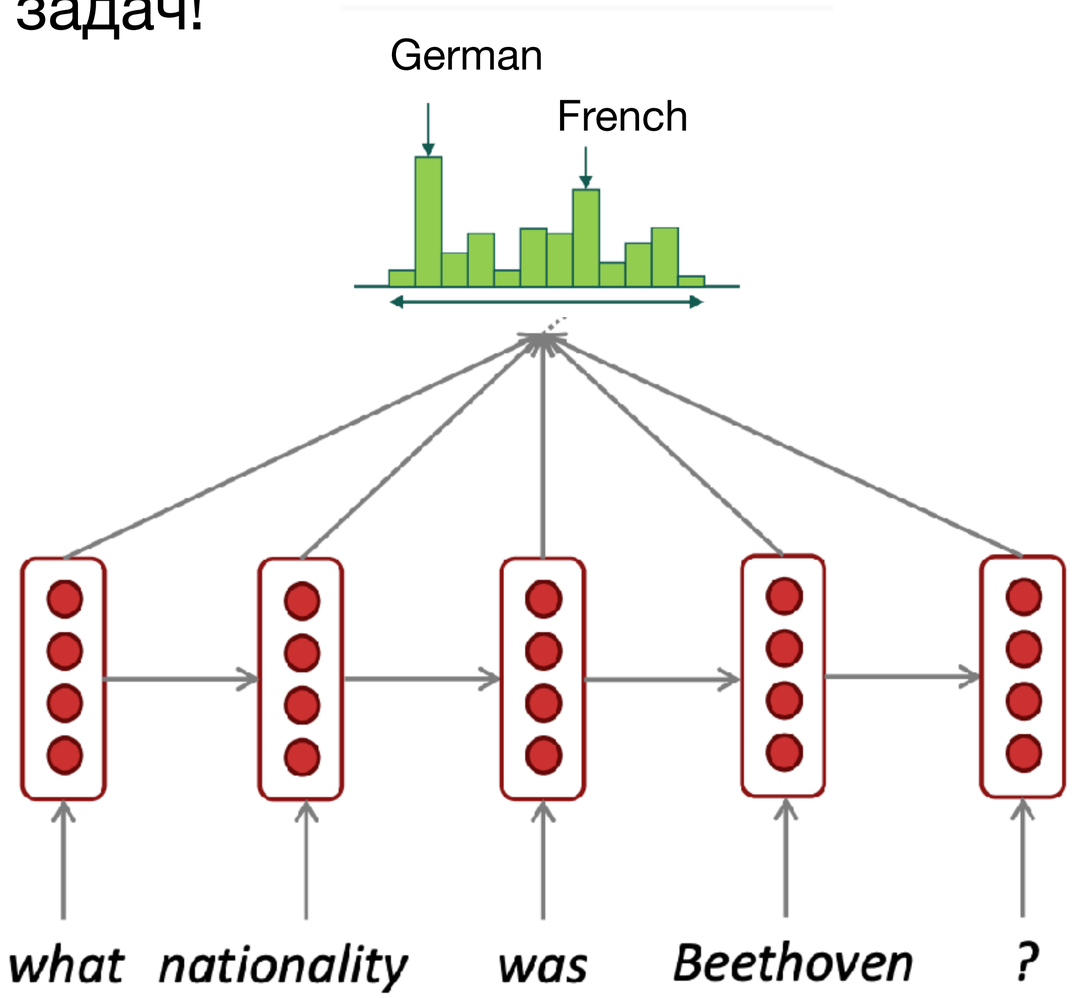


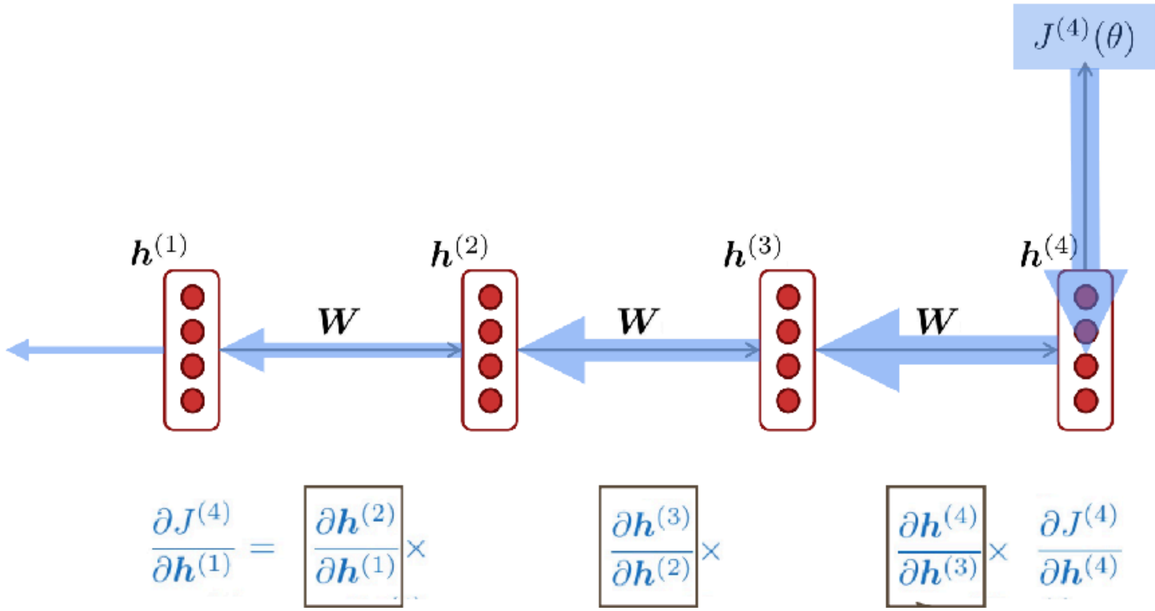
Image credit

Рекуррентные нейросети (RNN)

Проблемы?

- Медленно
- Vanishing gradients

Vanishing gradients (затухающие градиенты) — это проблема, которая возникает при обучении глубоких нейронных сетей, особенно в рекуррентных нейронных сетях (RNN) и многослойных полносвязных сетях. Суть этой проблемы заключается в том, что градиенты, используемые для обновления весов во время обратного распространения, становятся слишком малыми на ранних слоях сети, и веса перестают обновляться.



LM task: *When she tried to print her tickets, she found that the printer was out of toner. She went to the stationery store to buy more toner. It was very overpriced. After installing the toner into the printer, she finally printed her _____*

Image credit

Рекуррентные нейросети (RNN)

Проблемы?

- Медленно
- Vanishing gradients
- Exploding gradients? Solution: gradients clipping

Exploding gradients (взрывающиеся градиенты) — это проблема, противоположная затухающим градиентам, возникающая при обучении глубоких нейронных сетей. Взрывающиеся градиенты появляются, когда градиенты становятся слишком большими во время обратного распространения, что приводит к резкому увеличению весов и неустойчивому поведению сети. Эта проблема чаще всего встречается в рекуррентных нейронных сетях (RNN)

Ограничение градиентов (Gradient Clipping): Метод ограничения градиентов заключается в установке максимального порога для значений градиентов. Если градиент превышает заданный порог, он "обрезается" до этого порога. Это позволяет держать градиенты под контролем и избегать их взрывного роста. Например, в PyTorch это можно сделать так:

torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)

Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|}\hat{\mathbf{g}}$
end if

min-char-rnn.py gist: 112 lines of Python

```python
"""
Minimal character-level Vanilla RNN model. Written by Andrej Karpathy (@karpathy)
BSD License
"""
import numpy as np

# data I/O
data = open('input.txt', 'r').read() # should be simple plain text file
chars = list(set(data))
data_size, vocab_size = len(data), len(chars)
print 'data has %d characters, %d unique.' % (data_size, vocab_size)
char_to_ix = { ch:i for i,ch in enumerate(chars) }
ix_to_char = { i:ch for i,ch in enumerate(chars) }

# hyperparameters
hidden_size = 100 # size of hidden layer of neurons
seq_length = 25 # number of steps to unroll the RNN for
learning_rate = 1e-1

# model parameters
Wxh = np.random.randn(hidden_size, vocab_size)*0.01 # input to hidden
Whh = np.random.randn(hidden_size, hidden_size)*0.01 # hidden to hidden
Why = np.random.randn(vocab_size, hidden_size)*0.01 # hidden to output
bh = np.zeros((hidden_size, 1)) # hidden bias
by = np.zeros((vocab_size, 1)) # output bias

def lossFun(inputs, targets, hprev):
  """
  inputs,targets are both list of integers.
  hprev is Hx1 array of initial hidden state
  returns the loss, gradients on model parameters, and last hidden state
  """
  xs, hs, ys, ps = {}, {}, {}, {}
  hs[-1] = np.copy(hprev)
  loss = 0
  # forward pass
  for t in xrange(len(inputs)):
    xs[t] = np.zeros((vocab_size,1)) # encode in 1-of-k representation
    xs[t][inputs[t]] = 1
    hs[t] = np.tanh(np.dot(Wxh, xs[t]) + np.dot(Whh, hs[t-1]) + bh) # hidden state
    ys[t] = np.dot(Why, hs[t]) + by # unnormalized log probabilities for next chars
    ps[t] = np.exp(ys[t]) / np.sum(np.exp(ys[t])) # probabilities for next chars
    loss += -np.log(ps[t][targets[t],0]) # softmax (cross-entropy loss)
  # backward pass: compute gradients going backwards
  dWxh, dWhh, dWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
  dbh, dby = np.zeros_like(bh), np.zeros_like(by)
  dhnext = np.zeros_like(hs[0])
  for t in reversed(xrange(len(inputs))):
    dy = np.copy(ps[t])
    dy[targets[t]] -= 1 # backprop into y
    dWhy += np.dot(dy, hs[t].T)
    dby += dy
    dh = np.dot(Why.T, dy) + dhnext # backprop into h
    dhraw = (1 - hs[t] * hs[t]) * dh # backprop through tanh nonlinearity
    dbh += dhraw
    dWxh += np.dot(dhraw, xs[t].T)
    dWhh += np.dot(dhraw, hs[t-1].T)
    dhnext = np.dot(Whh.T, dhraw)
  for dparam in [dWxh, dWhh, dWhy, dbh, dby]:
    np.clip(dparam, -5, 5, out=dparam) # clip to mitigate exploding gradients
  return loss, dWxh, dWhh, dWhy, dbh, dby, hs[len(inputs)-1]

def sample(h, seed_ix, n):
  """
  sample a sequence of integers from the model
  h is memory state, seed_ix is seed letter for first time step
  """
  x = np.zeros((vocab_size, 1))
  x[seed_ix] = 1
  ixes = []
  for t in xrange(n):
    h = np.tanh(np.dot(Wxh, x) + np.dot(Whh, h) + bh)
    y = np.dot(Why, h) + by
    p = np.exp(y) / np.sum(np.exp(y))
    ix = np.random.choice(range(vocab_size), p=p.ravel())
    x = np.zeros((vocab_size, 1))
    x[ix] = 1
    ixes.append(ix)
  return ixes

n, p = 0, 0
mWxh, mWhh, mWhy = np.zeros_like(Wxh), np.zeros_like(Whh), np.zeros_like(Why)
mbh, mby = np.zeros_like(bh), np.zeros_like(by) # memory variables for Adagrad
smooth_loss = -np.log(1.0/vocab_size)*seq_length # loss at iteration 0
while True:
  # prepare inputs (we're sweeping from left to right in steps seq_length long)
  if p+seq_length+1 >= len(data) or n == 0:
    hprev = np.zeros((hidden_size,1)) # reset RNN memory
    p = 0 # go from start of data
  inputs = [char_to_ix[ch] for ch in data[p:p+seq_length]]
  targets = [char_to_ix[ch] for ch in data[p+1:p+seq_length+1]]

  # sample from the model now and then
  if n % 100 == 0:
    sample_ix = sample(hprev, inputs[0], 200)
    txt = ''.join(ix_to_char[ix] for ix in sample_ix)
    print '----\n %s \n----' % (txt, )

  # forward seq_length characters through the net and fetch gradient
  loss, dWxh, dWhh, dWhy, dbh, dby, hprev = lossFun(inputs, targets, hprev)
  smooth_loss = smooth_loss * 0.999 + loss * 0.001
  if n % 100 == 0: print 'iter %d, loss: %f' % (n, smooth_loss) # print progress

  # perform parameter update with Adagrad
  for param, dparam, mem in zip([Wxh, Whh, Why, bh, by],
                                [dWxh, dWhh, dWhy, dbh, dby],
                                [mWxh, mWhh, mWhy, mbh, mby]):
    mem += dparam * dparam
    param += -learning_rate * dparam / np.sqrt(mem + 1e-8) # adagrad update

  p += seq_length # move data pointer
  n += 1 # iteration counter
```

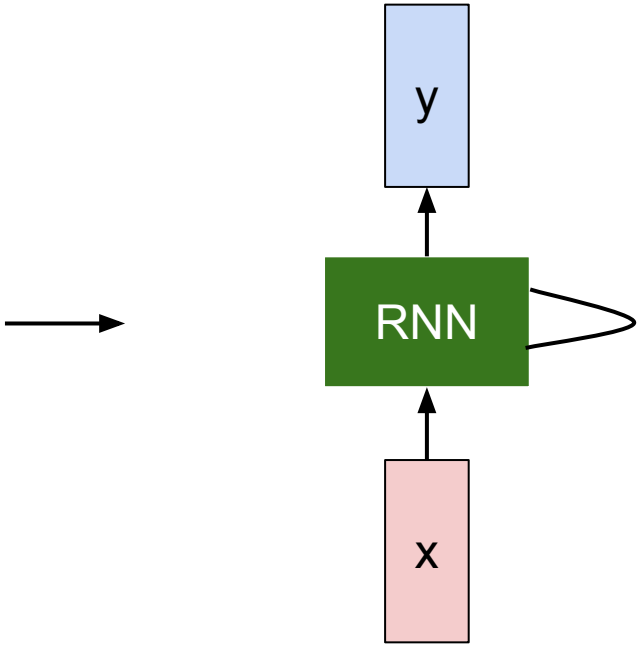
(https://gist.github.com/karpathy/d4dee566867f8291f086)

THE SONNETS

by William Shakespeare

From fairest creatures we desire increase,
That thereby beauty's rose might never die,
But as the riper should by time decease,
His tender heir might bear his memory:
But thou, contracted to thine own bright eyes,
Feed'st thy light's flame with self-substantial fuel,
Making a famine where abundance lies,
Thyself thy foe, to thy sweet self too cruel:
Thou that art now the world's fresh ornament,
And only herald to the gaudy spring,
Within thine own bud buriest thy content,
And tender churl mak'st waste in niggarding:
    Pity the world, or else this glutton be,
    To eat the world's due, by the grave and thee.

When forty winters shall besiege thy brow,
And dig deep trenches in thy beauty's field,
Thy youth's proud livery so gazed on now,
Will be a tatter'd weed of small worth held:
Then being asked, where all thy beauty lies,
Where all the treasure of thy lusty days;
To say, within thine own deep sunken eyes,
Were an all-eating shame, and thriftless praise.
How much more praise deserv'd thy beauty's use,
If thou couldst answer 'This fair child of mine
Shall sum my count, and make my old excuse,'
Proving his beauty by succession thine!
    This were to be new made when thou art old,
    And see thy blood warm when thou feel'st it cold.



at first:

```
tyntd-iafhatawiaoihrdemot  lytdws  e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrgd t o idoe ns,smtt   h ne etie h,hregtrs nigtike,aoaenns lng
```

train more

```
"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuwy fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."
```

train more

```
Aftair fall unsuch that the hall for Prince Velzonski's that me of
her hearly, and behs to so arwage fiving were to it beloge, pavu say falling misfort
how, and Gogition is so overelical and ofter.
```

train more

```
"Why do what that day," replied Natasha, and wishing to himself the fact the
princess, Princess Mary was easier, fed in had oftened him.
Pierre aking his soul came to the packs and drove up his father-in-law women.
```

PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

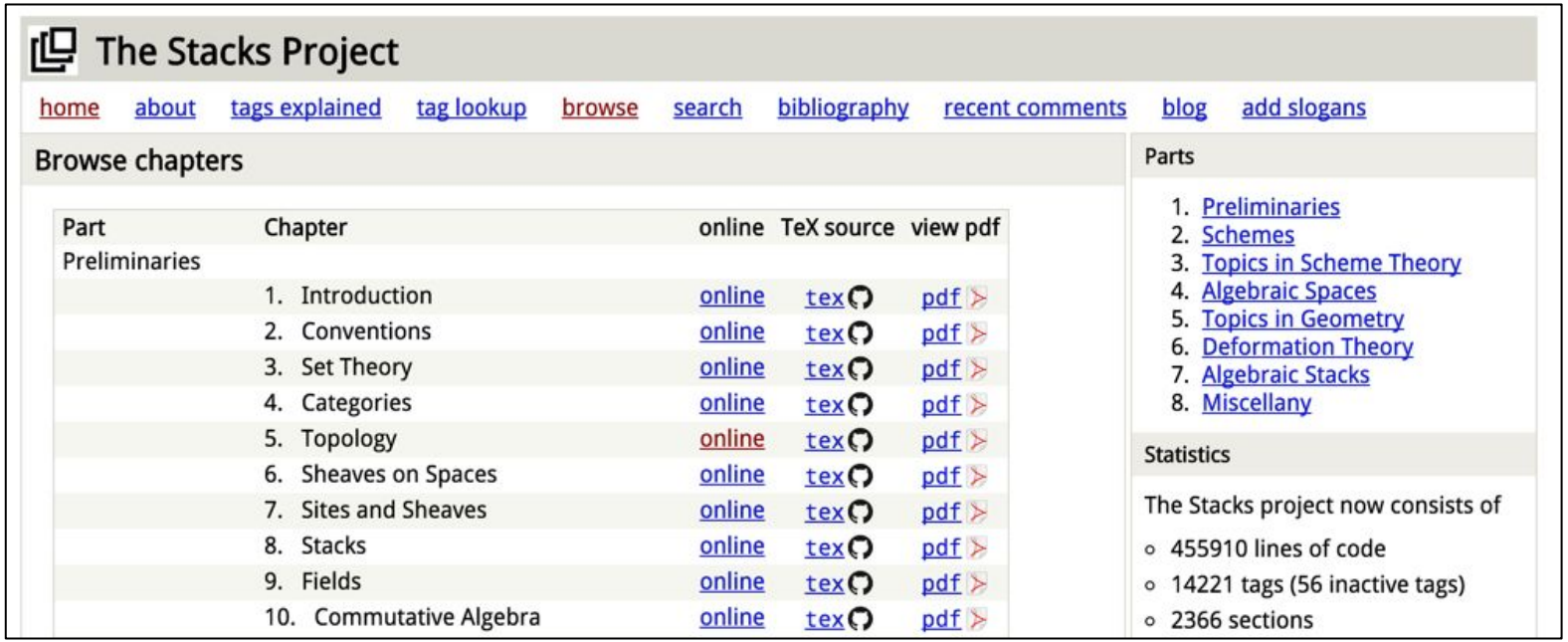
Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.

VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.

The Stacks Project: open source algebraic geometry textbook



Latex source

For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \text{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\text{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\text{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\text{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\text{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \text{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces,étale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

Lemma 0.1. *Assume (3) and (3) by the construction in the description.*

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{Proj}_X(\mathcal{A}) =$ $\text{Spec}(B)$ over U compatible with the complex

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \to \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition **??** *(without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S. Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem*

(1) *f is locally of finite type. Since $S = \text{Spec}(R)$ and $Y = \text{Spec}(R)$.*

Proof. This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\ldots,n} U_i$ be the scheme X over S at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\ldots,0}$.

Lemma 0.2. *Let X be a locally Noetherian scheme over S, $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}^n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq \mathfrak{p}$ is a subset of $\mathcal{J}_{n,0} \circ \overline{A}_2$ works.*

Lemma 0.3. *In Situation* **??**. *Hence we may assume $\mathfrak{q}' = 0$.*

Proof. We will use the property we see that $\mathfrak{p}$ is the mext functor (**??**). On the other hand, by Lemma **??** we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F-algebra where δ_{n+1} is a scheme over S. □

Proof. Omitted. □

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

.

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules. □

Lemma 0.2. *This is an integer $\mathcal{Z}$ is injective.*

Proof. See Spaces, Lemma ??. □

Lemma 0.3. *Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.*

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let $\mathcal{F}$ be a quasi-coherent sheaf of $\mathcal{O}_X$-modules. The following are equivalent

(1) $\mathcal{F}$ is an algebraic space over S.
(2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type. □

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

$$\begin{array}{ccc} \mathcal{S} & \longrightarrow & \\ \downarrow & & \\ \xi & \longrightarrow & \mathcal{O}_{X'} \\ & & \uparrow \\ \mathrm{gor}_s & & \end{array} \qquad \begin{array}{ccc} & = \alpha' & \longrightarrow \\ & \updownarrow & \\ & = \alpha' & \longrightarrow \alpha \end{array} \qquad \begin{array}{c} X \\ \downarrow \\ \mathrm{d}(\mathcal{O}_{X_{X/k}}, \mathcal{G}) \end{array}$$

$$\mathrm{Spec}(K_\psi) \qquad \mathrm{Mor}_{Sets}$$

is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

□

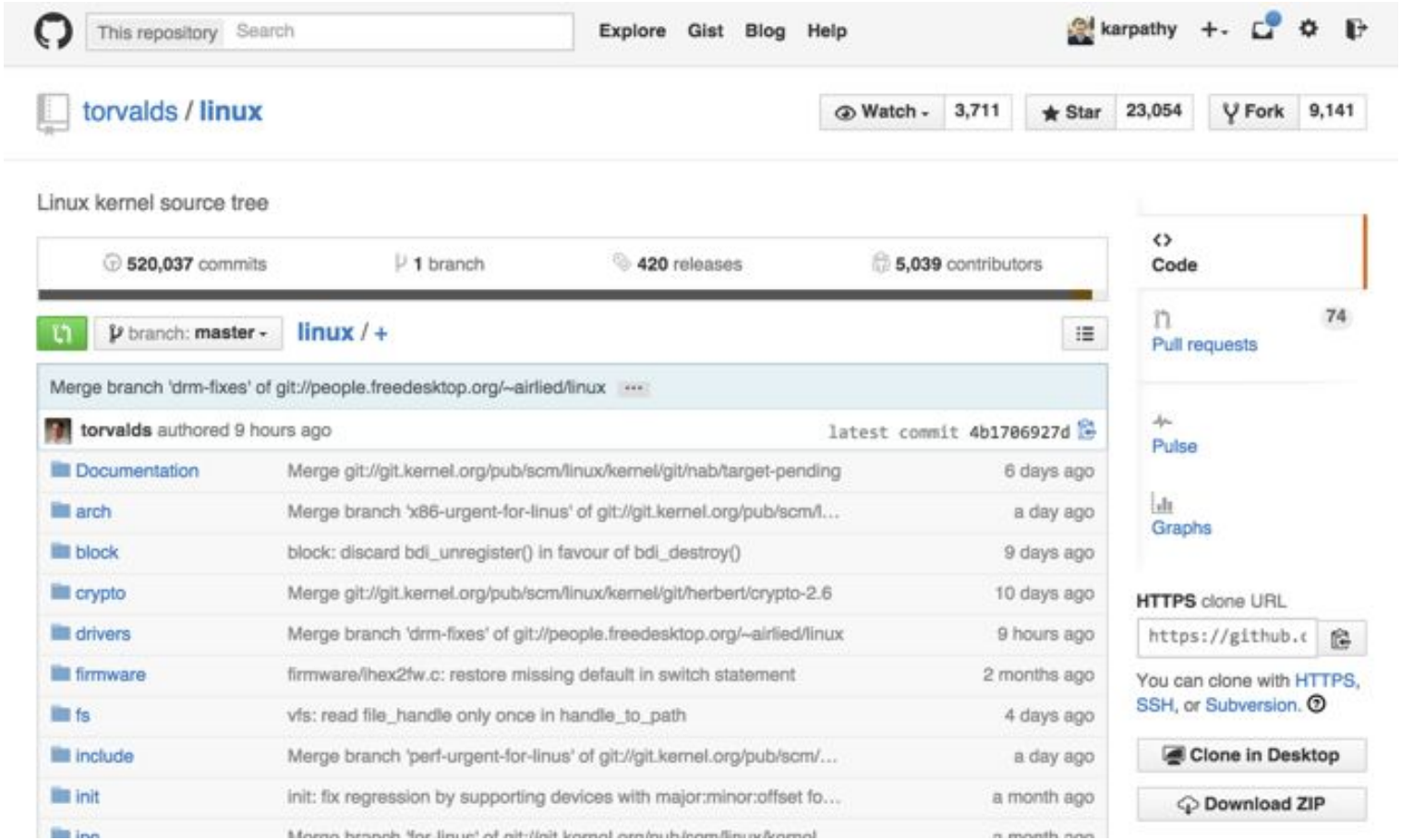
Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U. □

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas ??.
A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} \quad \text{-1}(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_t}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{v}})$$

is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.
The property $\mathcal{F}$ is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.
If $\mathcal{F}$ is a scheme theoretic image points. □

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.


This repository
Search
Explore
Gist
Blog
Help
karpathy
torvalds / linux
Watch 3,711
Star 23,054
Fork 9,141
Linux kernel source tree
520,037 commits
1 branch
420 releases
5,039 contributors
branch: master
linux / +
Merge branch 'drm-fixes' of git://people.freedesktop.org/~airlied/linux
torvalds authored 9 hours ago
latest commit 4b1706927d
Documentation Merge git://git.kernel.org/pub/scm/linux/kernel/git/nab/target-pending 6 days ago
arch Merge branch 'x86-urgent-for-linus' of git://git.kernel.org/pub/scm/l... a day ago
block block: discard bdi_unregister() in favour of bdi_destroy() 9 days ago
crypto Merge git://git.kernel.org/pub/scm/linux/kernel/git/herbert/crypto-2.6 10 days ago
drivers Merge branch 'drm-fixes' of git://people.freedesktop.org/~airlied/linux 9 hours ago
firmware firmware/ihex2fw.c: restore missing default in switch statement 2 months ago
fs vfs: read file_handle only once in handle_to_path 4 days ago
include Merge branch 'perf-urgent-for-linus' of git://git.kernel.org/pub/scm/... a day ago
init init: fix regression by supporting devices with major:minor:offset fo... a month ago
Code
74
Pull requests
Pulse
Graphs
HTTPS clone URL
https://github.c
You can clone with HTTPS, SSH, or Subversion.
Clone in Desktop
Download ZIP

```
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000ffffffff8) & 0x000000f) << 8;
    if (count == 0)
      sub(pid, ppc_md.kexec_handle, 0x20000000);
    pipe_set_bytes(i, 0);
  }
  /* Free our user pages pointer to place camera if all dash */
  subsystem_info = &of_changes[PAGE_SIZE];
  rek_controls(offset, idx, &soffset);
  /* Now we want to deliberately put it to device */
  control_check_polarity(&context, val, 0);
  for (i = 0; i < COUNTER; i++)
    seq_puts(s, "policy ");
}
```

Generated C code

```
/*
 *  Copyright (c) 2006-2010, Intel Mobile Communications.  All rights reserved.
 *
 *   This program is free software; you can redistribute it and/or modify it
 * under the terms of the GNU General Public License version 2 as published by
 * the Free Software Foundation.
 *
 *        This program is distributed in the hope that it will be useful,
 * but WITHOUT ANY WARRANTY; without even the implied warranty of
 *   MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the
 *
 *  GNU General Public License for more details.
 *
 *   You should have received a copy of the GNU General Public License
 *    along with this program; if not, write to the Free Software Foundation,
 *  Inc., 675 Mass Ave, Cambridge, MA 02139, USA.
 */

#include <linux/kexec.h>
#include <linux/errno.h>
#include <linux/io.h>
#include <linux/platform_device.h>
#include <linux/multi.h>
#include <linux/ckevent.h>

#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>
```

```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>

#define REG_PG    vesa_slot_addr_pack
#define PFM_NOCOMP  AFSR(0, load)
#define STACK_DDR(type)     (func)

#define SWAP_ALLOCATE(nr)     (e)
#define emulate_sigs()  arch_get_unaligned_child()
#define access_rw(TST)  asm volatile("movd %%esp, %0, %3" : : "r" (0));   \
  if (__type & DO_READ)

static void stat_PC_SEC __read_mostly offsetof(struct seq_argsqueue, \
          pC>[1]);

static void
os_prefix(unsigned long sys)
{
#ifdef CONFIG_PREEMPT
  PUT_PARAM_RAID(2, sel) = get_state_state();
  set_pid_sum((unsigned long)state, current_state_str(),
           (unsigned long)-1->lr_full; low;
}
```

OpenAI GPT-2 generated text

source

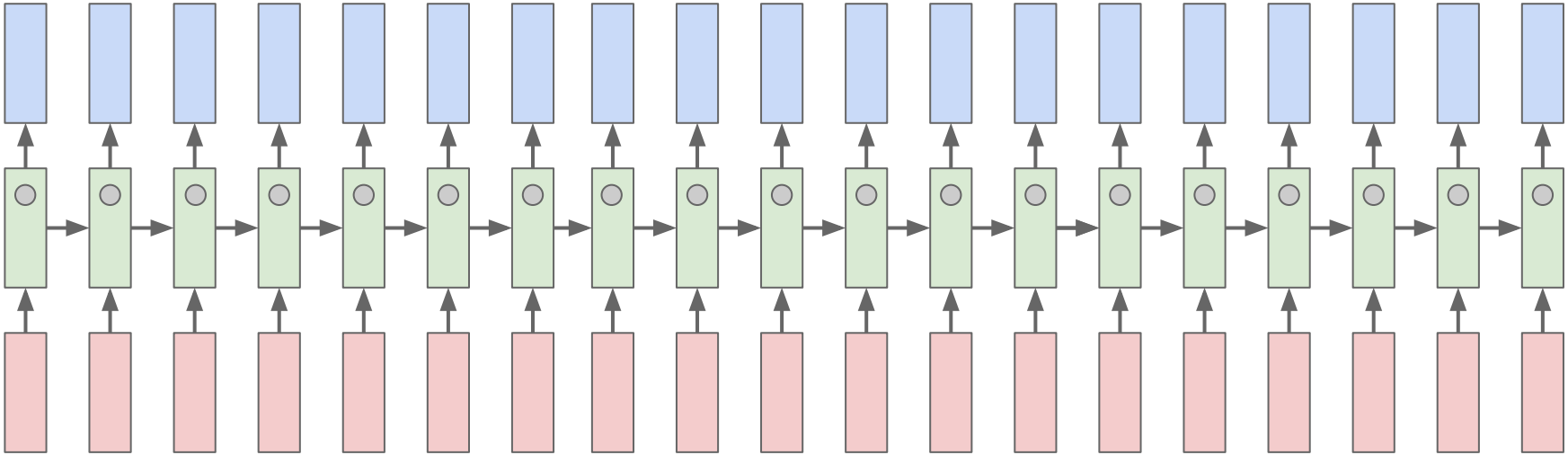
Input: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

Output: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

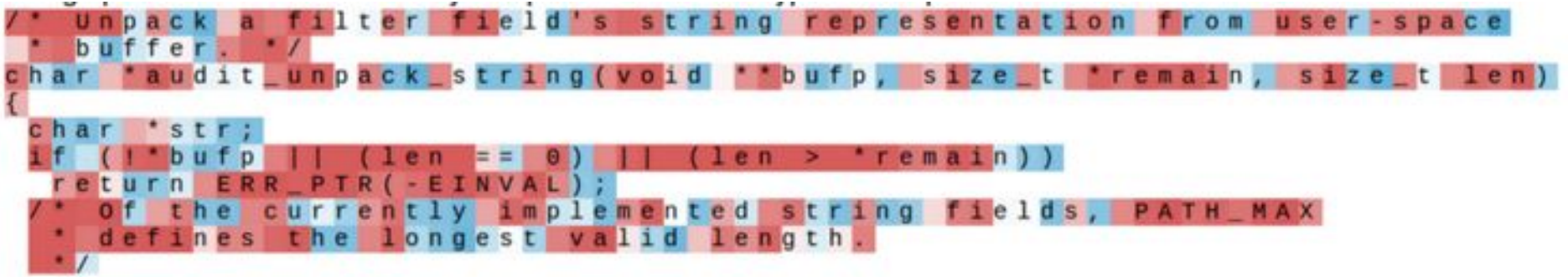
Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Searching for interpretable cells

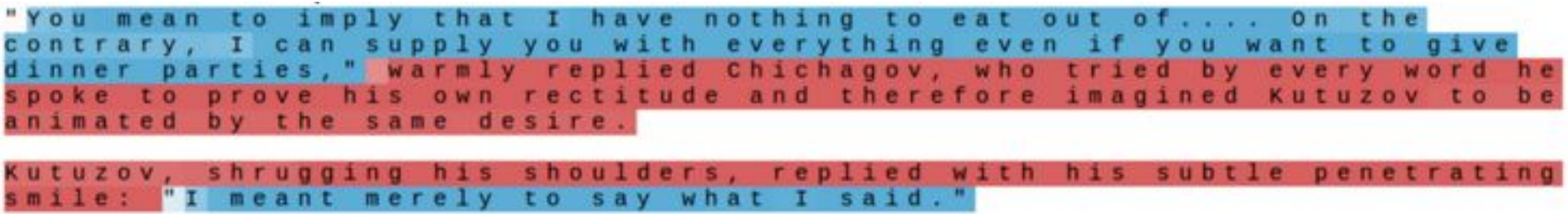


Searching for interpretable cells



Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

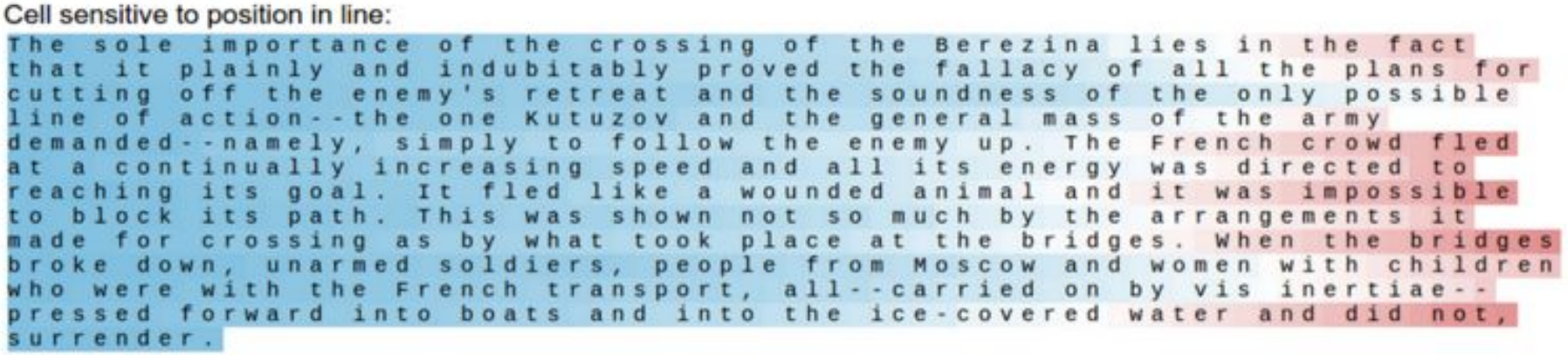
Searching for interpretable cells



quote detection cell

Обнаружение цитат (quote detection) — это задача в обработке естественного языка (NLP), направленная на автоматическое определение и извлечение текстовых фрагментов, представляющих собой цитаты, из больших объемов текстовых данных

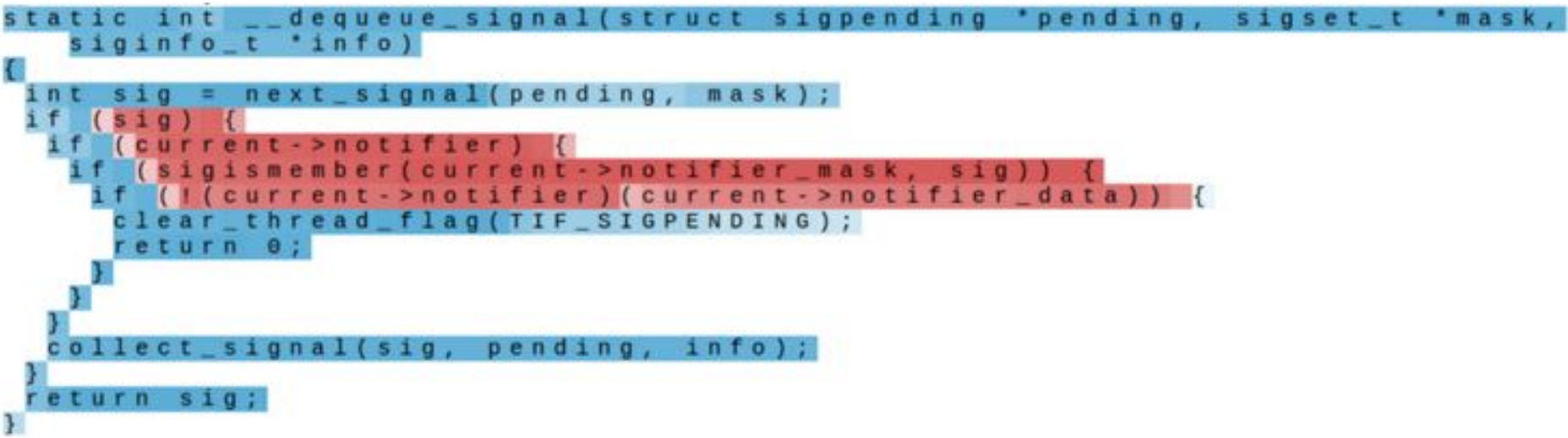
Searching for interpretable cells



line length tracking cell

Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

Searching for interpretable cells



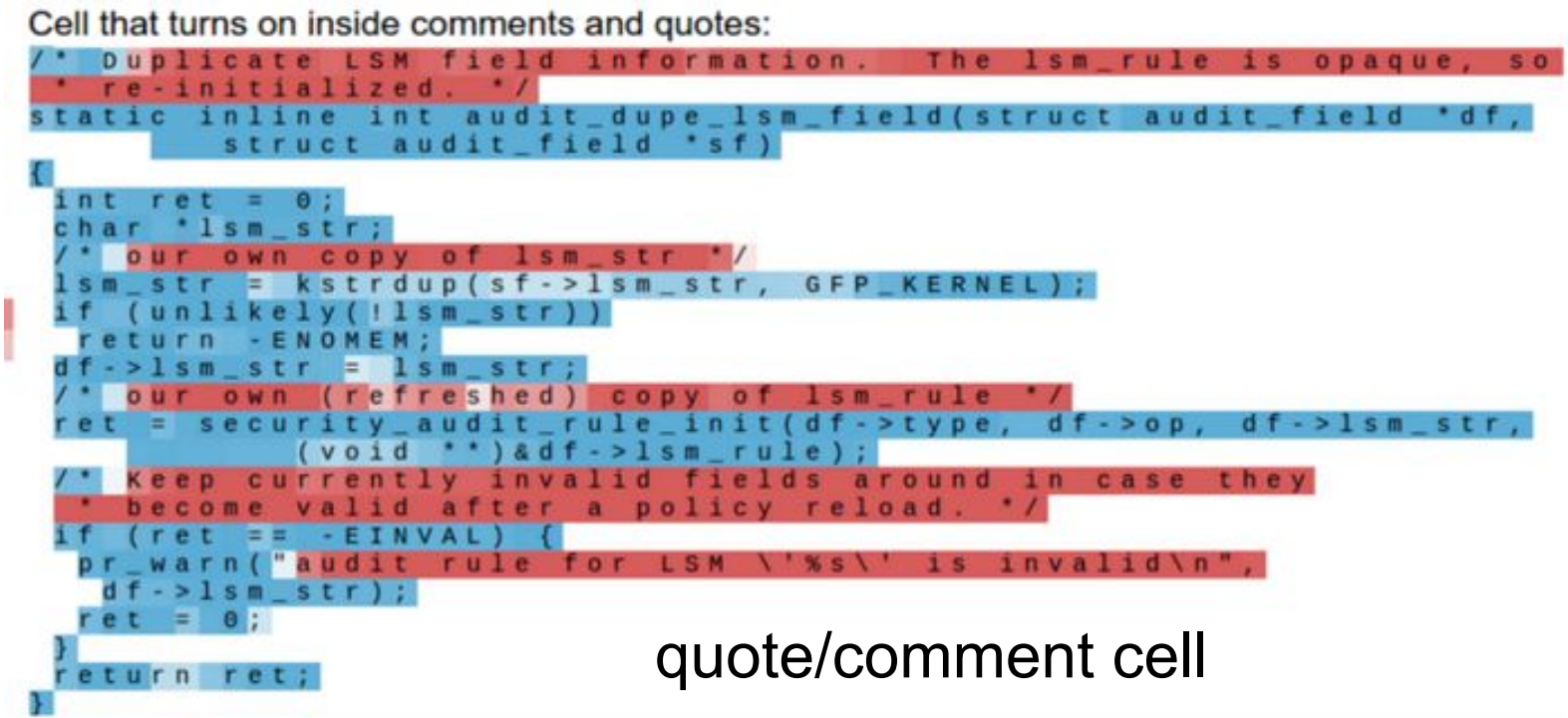
```
static int __dequeue_signal(struct sigpending *pending, sigset_t *mask,
        siginfo_t *info)
{
  int sig = next_signal(pending, mask);
  if (sig) {
    if (current->notifier) {
      if (sigismember(current->notifier_mask, sig)) {
        if (!(current->notifier)(current->notifier_data)) {
          clear_thread_flag(TIF_SIGPENDING);
          return 0;
        }
      }
    }
    collect_signal(sig, pending, info);
  }
  return sig;
}
```

if statement cell

Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

Searching for interpretable cells

Cell that turns on inside comments and quotes:

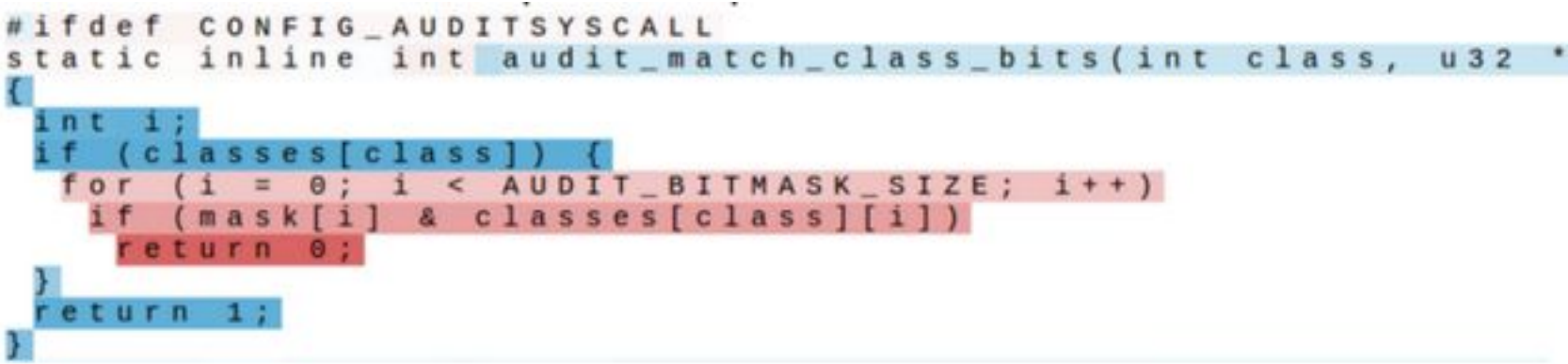


```
/* Duplicate LSM field information.  The lsm_rule is opaque, so
 * re-initialized. */
static inline int audit_dupe_lsm_field(struct audit_field *df,
                                       struct audit_field *sf)
{
  int ret = 0;
  char *lsm_str;
  /* our own copy of lsm_str */
  lsm_str = kstrdup(sf->lsm_str, GFP_KERNEL);
  if (unlikely(!lsm_str))
    return -ENOMEM;
  df->lsm_str = lsm_str;
  /* our own (refreshed) copy of lsm_rule */
  ret = security_audit_rule_init(df->type, df->op, df->lsm_str,
                                 (void **)&df->lsm_rule);
  /* Keep currently invalid fields around in case they
   * become valid after a policy reload. */
  if (ret == -EINVAL) {
    pr_warn("audit rule for LSM \'%s\' is invalid\n",
            df->lsm_str);
    ret = 0;
  }
  return ret;
}
```

quote/comment cell

Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

Searching for interpretable cells



code depth cell

Karpathy, Johnson, and Fei-Fei: Visualizing and Understanding Recurrent Networks, ICLR Workshop 2016

RNN tradeoffs

RNN Advantages:

- Can process any length input
- Computation for step *t* can (in theory) use information from many steps back
- Model size doesn't increase for longer input
- Same weights applied on every timestep, so there is symmetry in how inputs are processed.

RNN Disadvantages:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back

LSTM

Vanilla RNN постоянно переписывает $\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h \boldsymbol{h}^{(t-1)} + \boldsymbol{W}_x \boldsymbol{x}^{(t)} + \boldsymbol{b}\right)$

Идея: добавить “память” $\boldsymbol{c}^{(t)}$

LSTM

Vanilla RNN постоянно переписывает $\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h \boldsymbol{h}^{(t-1)} + \boldsymbol{W}_x \boldsymbol{x}^{(t)} + \boldsymbol{b}\right)$

Идея: добавить “память” $\boldsymbol{c}^{(t)}$

Новая информация

$$\tilde{\boldsymbol{c}}^{(t)} = \tanh\left(\boldsymbol{W}_c \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_c \boldsymbol{x}^{(t)} + \boldsymbol{b}_c\right)$$

$$\boldsymbol{c}^{(t)} = \boldsymbol{f}^{(t)} \circ \boldsymbol{c}^{(t-1)} + \boldsymbol{i}^{(t)} \circ \tilde{\boldsymbol{c}}^{(t)}$$

$$\boldsymbol{h}^{(t)} = \boldsymbol{o}^{(t)} \circ \tanh \boldsymbol{c}^{(t)}$$

All these are vectors of same length n

Image credit

LSTM

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All these are vectors of same length n

Image credit

LSTM

Vanilla RNN постоянно переписывает $h^{(t)} = \sigma\left(W_h h^{(t-1)} + W_x x^{(t)} + b\right)$

Идея: добавить “память” $c^{(t)}$

Sigmoid function: all gate values are between 0 and 1

Forget gate: контролируем сколько забыть $f^{(t)} = \sigma\left(W_f h^{(t-1)} + U_f x^{(t)} + b_f\right)$

Input gate: контролируем сколько записать $i^{(t)} = \sigma\left(W_i h^{(t-1)} + U_i x^{(t)} + b_i\right)$

Новая информация $\tilde{c}^{(t)} = \tanh\left(W_c h^{(t-1)} + U_c x^{(t)} + b_c\right)$

Можно записать новую и стереть старую

$$c^{(t)} = f^{(t)} \circ c^{(t-1)} + i^{(t)} \circ \tilde{c}^{(t)}$$

$$h^{(t)} = o^{(t)} \circ \tanh c^{(t)}$$

All these are vectors of same length n

Image credit

LSTM

Vanilla RNN постоянно переписывает $h^{(t)} = \sigma\left(W_h h^{(t-1)} + W_x x^{(t)} + b\right)$

Идея: добавить “память” $c^{(t)}$

Sigmoid function: all gate values are between 0 and 1

Forget gate: контролируем сколько забыть $f^{(t)} = \sigma\left(W_f h^{(t-1)} + U_f x^{(t)} + b_f\right)$

Input gate: контролируем сколько записать $i^{(t)} = \sigma\left(W_i h^{(t-1)} + U_i x^{(t)} + b_i\right)$

Output gate: контролируем сколько считать $o^{(t)} = \sigma\left(W_o h^{(t-1)} + U_o x^{(t)} + b_o\right)$

Новая информация $\tilde{c}^{(t)} = \tanh\left(W_c h^{(t-1)} + U_c x^{(t)} + b_c\right)$

Можно записать новую и стереть старую $c^{(t)} = f^{(t)} \circ c^{(t-1)} + i^{(t)} \circ \tilde{c}^{(t)}$

Считывание $h^{(t)} = o^{(t)} \circ \tanh c^{(t)}$

All these are vectors of same length *n*

Image credit

Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

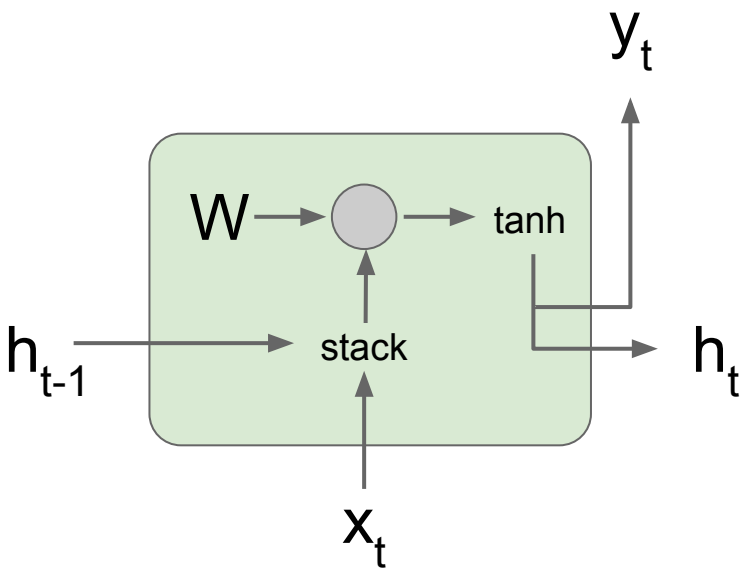
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Hochreiter and Schmidhuber, “Long Short Term Memory”, Neural Computation 1997

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013



$$
\begin{aligned}
h_t &= \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \\
&= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right) \\
&= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)
\end{aligned}
$$

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
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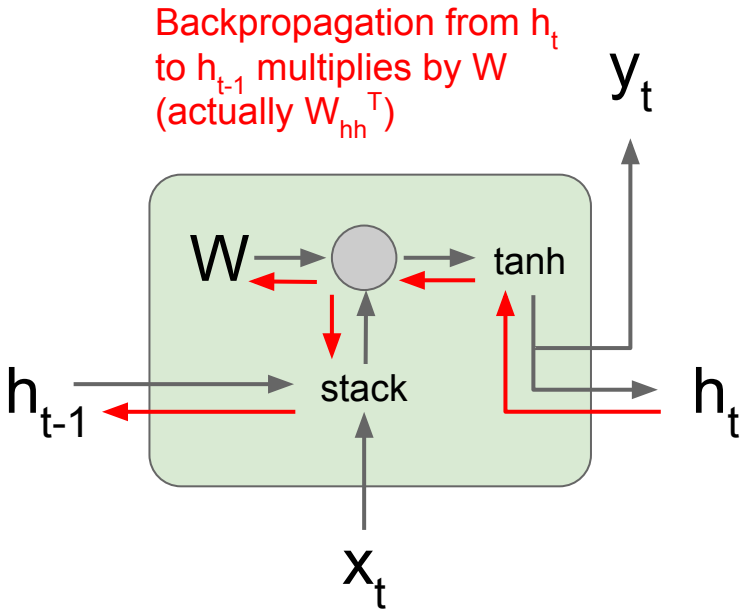

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$= \tanh\left((W_{hh} \quad W_{hx})\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$= \tanh\left(W\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

Vanilla RNN Gradient Flow

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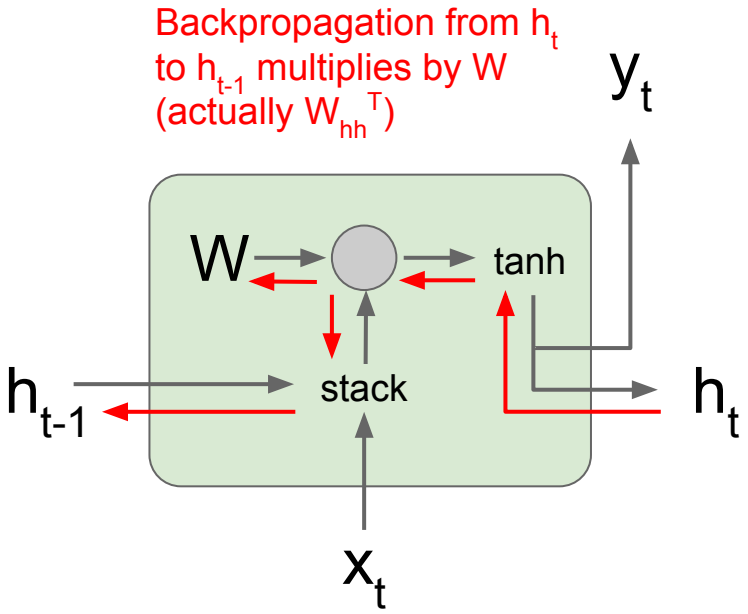

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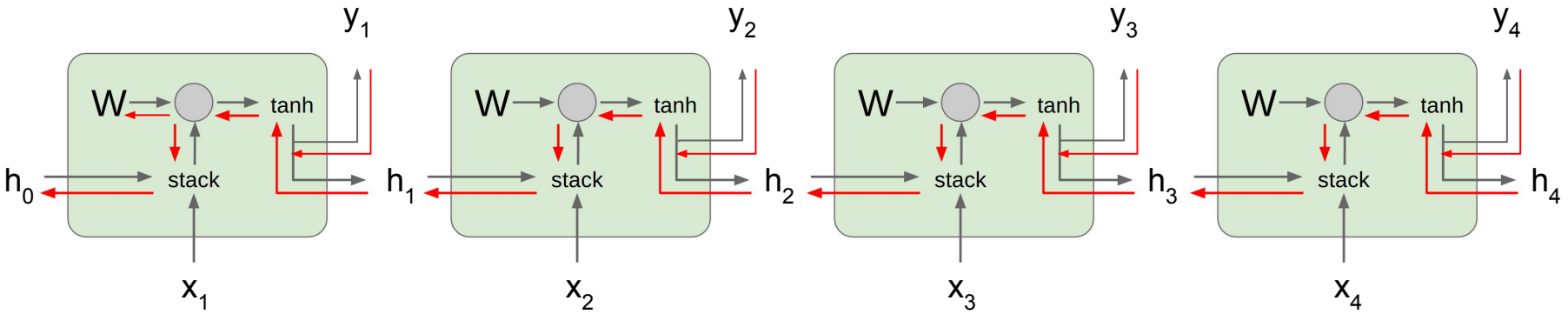
$$= \tanh\left((W_{hh} \quad W_{hx})\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$
$$= \tanh\left(W\begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$\frac{\partial h_t}{\partial h_{t-1}} = tanh'(W_{hh}h_{t-1} + W_{xh}x_t)W_{hh}$$

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013

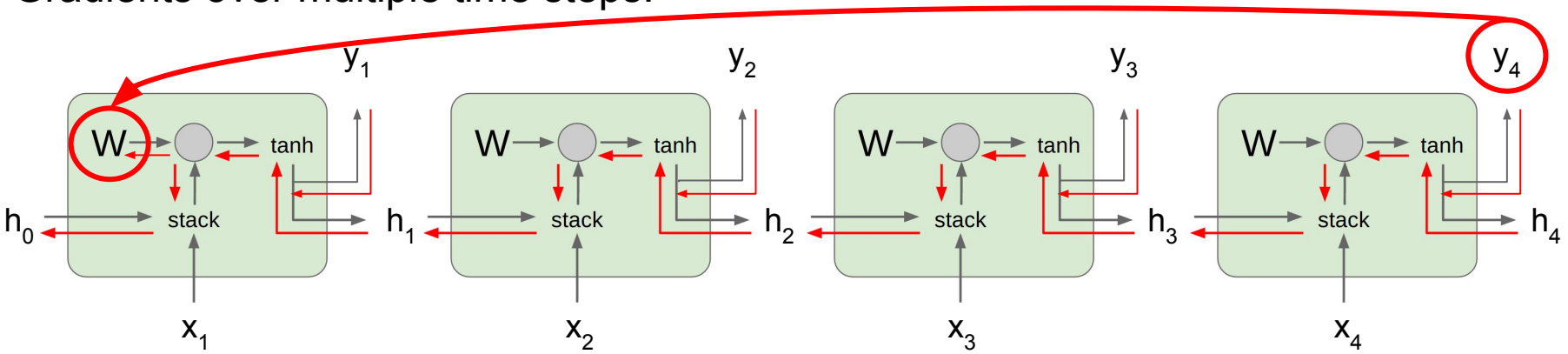


$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013

Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

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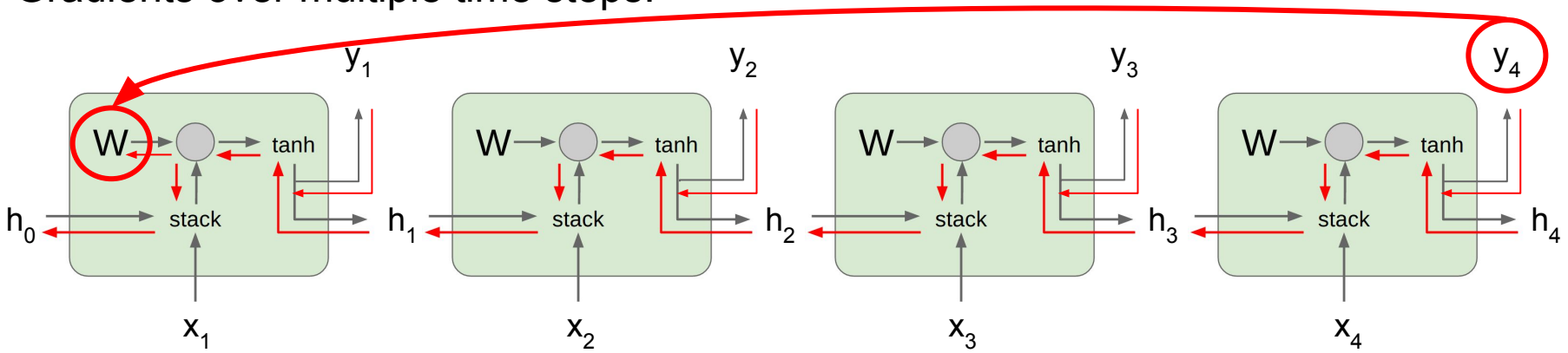
Gradients over multiple time steps:



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$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^{T} \frac{\partial h_t}{\partial h_{t-1}} \right) \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
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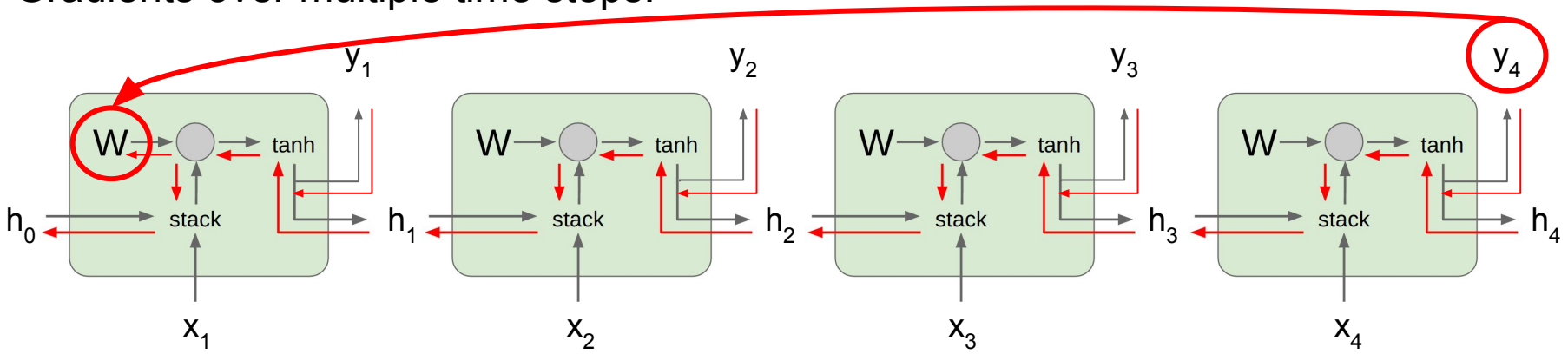
Gradients over multiple time steps:



$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\frac{\partial h_t}{\partial h_{t-1}} = tanh'(W_{hh} h_{t-1} + W_{xh} x_t) W_{hh}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \frac{\partial h_t}{\partial h_{t-1}} \cdots \frac{\partial h_1}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^{T} \frac{\partial h_t}{\partial h_{t-1}} \right) \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

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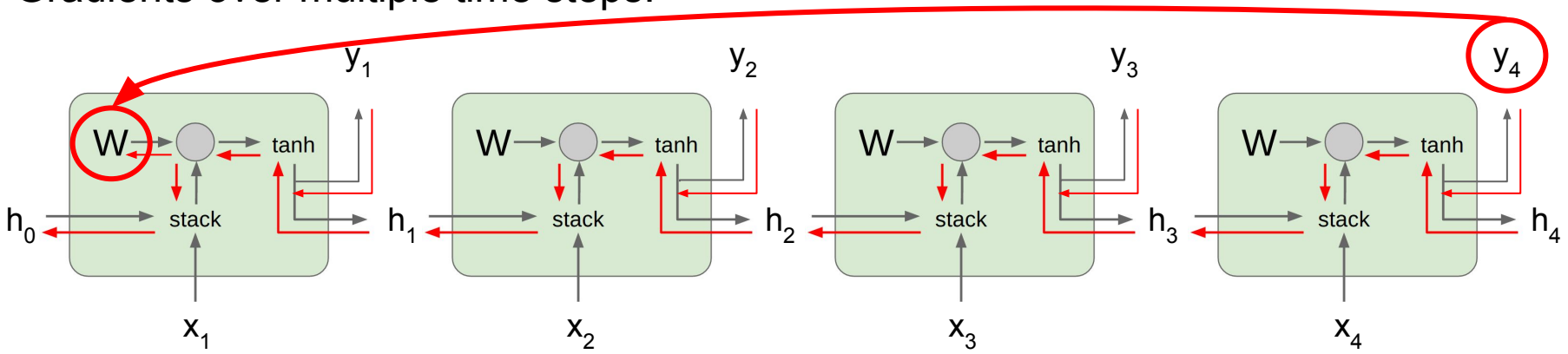


$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

Almost always < 1

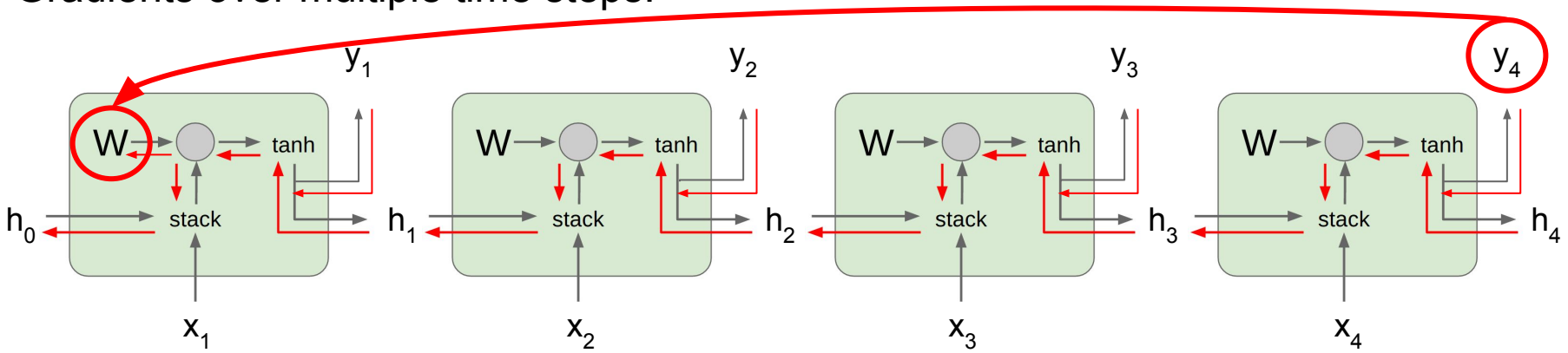
Vanishing gradients

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} \left(\prod_{t=2}^{T} tanh'\left(W_{hh} h_{t-1} + W_{xh} x_t\right) \right) W_{hh}^{T-1} \frac{\partial h_1}{\partial W}$$

Vanilla RNN Gradient Flow

Bengio et al, “Learning long-term dependencies with gradient descent is difficult”, IEEE Transactions on Neural Networks, 1994
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013

Gradients over multiple time steps:



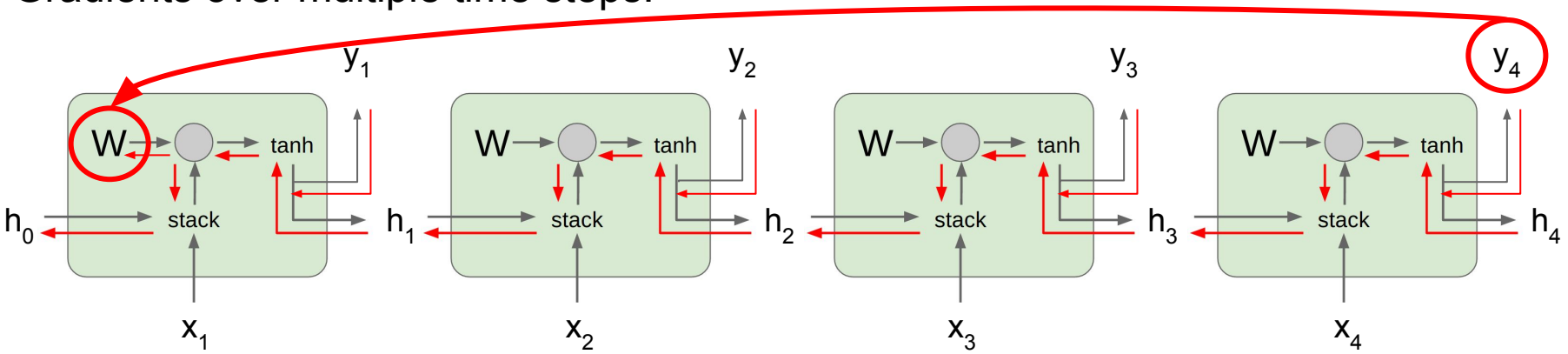
$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

What if we assumed no non-linearity?

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



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$$\frac{\partial L}{\partial W} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial W}$$

$$\frac{\partial L_T}{\partial W} = \frac{\partial L_T}{\partial h_T} W_{hh}^{T-1} \frac{\partial h_1}{\partial W}$$

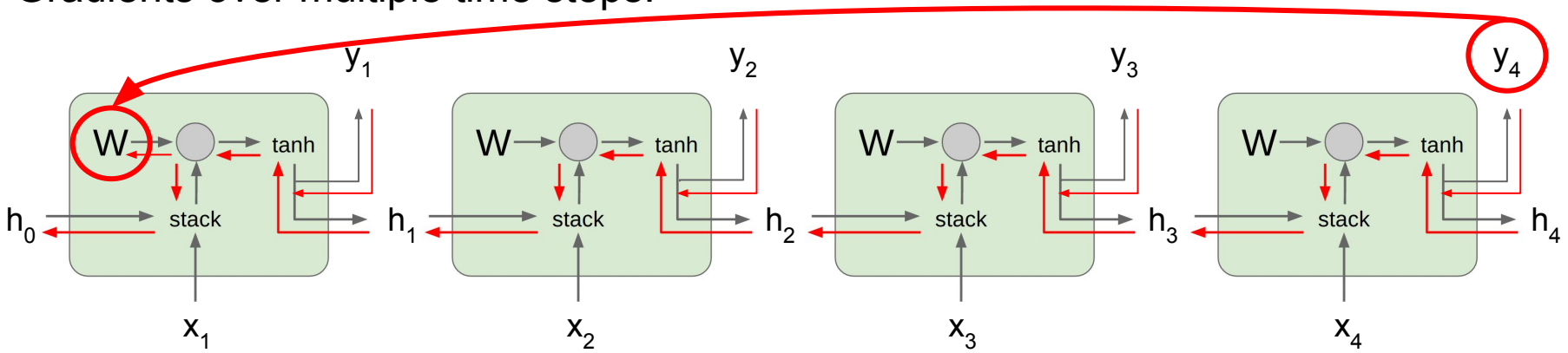
Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



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Largest singular value > 1:
Exploding gradients

→ **Gradient clipping**: Scale gradient if its norm is too big

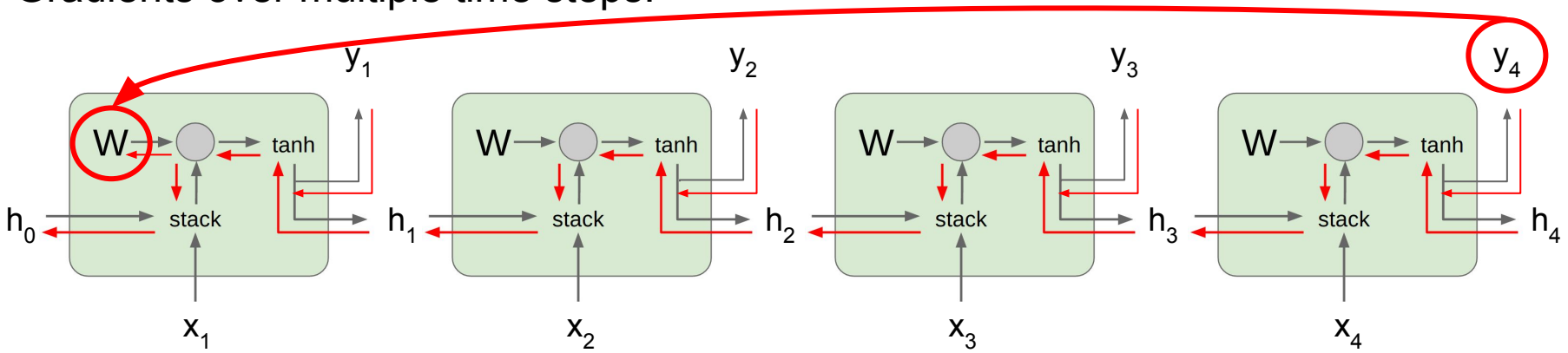
```
grad_norm = np.sum(grad * grad)
if grad_norm > threshold:
  grad *= (threshold / grad_norm)
```

Largest singular value < 1:
Vanishing gradients

Vanilla RNN Gradient Flow

Bengio et al, "Learning long-term dependencies with gradient descent is difficult", IEEE Transactions on Neural Networks, 1994
Pascanu et al, "On the difficulty of training recurrent neural networks", ICML 2013

Gradients over multiple time steps:



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Largest singular value > 1:
Exploding gradients

Largest singular value < 1:
Vanishing gradients

→ Change RNN architecture

Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

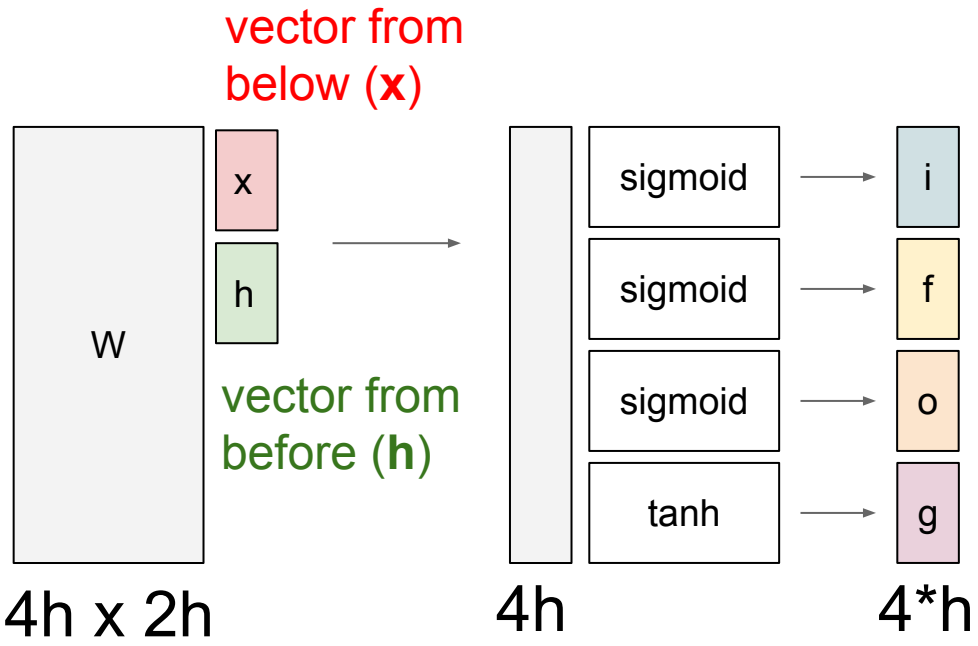
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Hochreiter and Schmidhuber, “Long Short Term Memory”, Neural Computation 1997

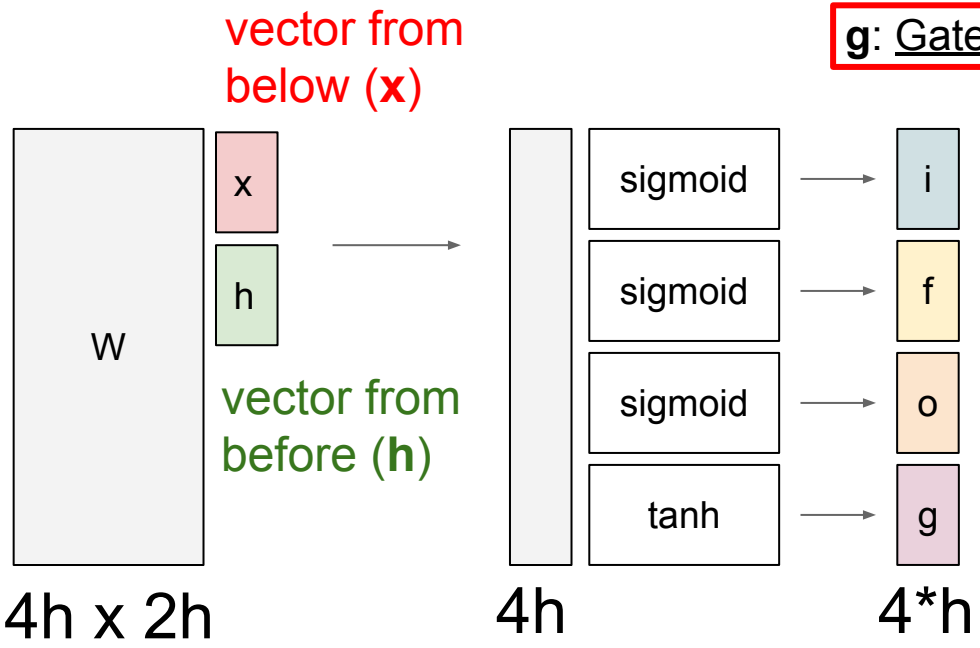
Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



g: Gate gate (?), How much to write to cell

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

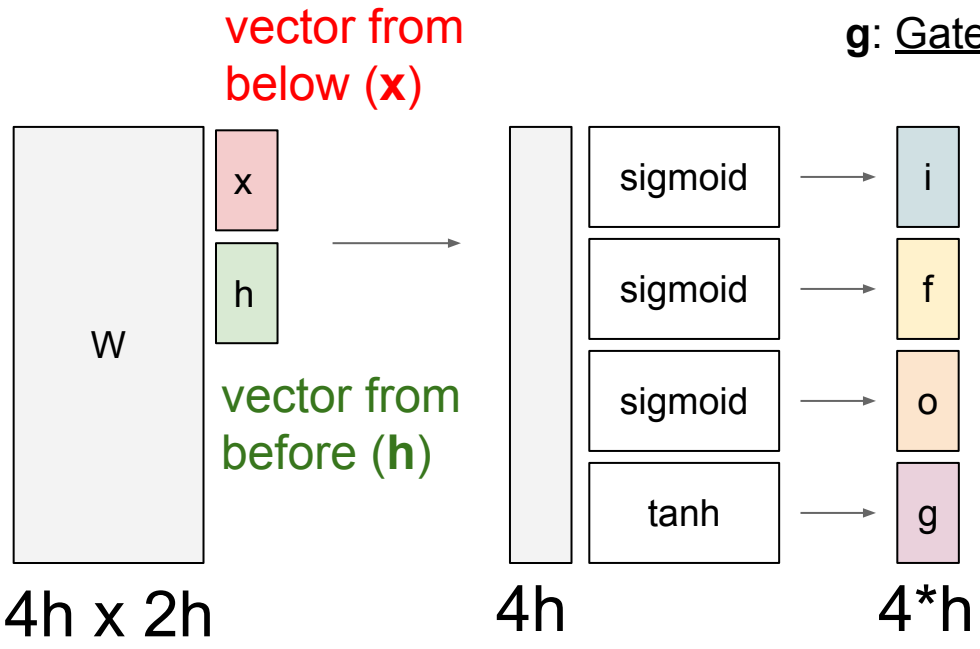
$$h_t = o \odot \tanh(c_t)$$

Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

i: Input gate, whether to write to cell

g: Gate gate (?), How much to write to cell



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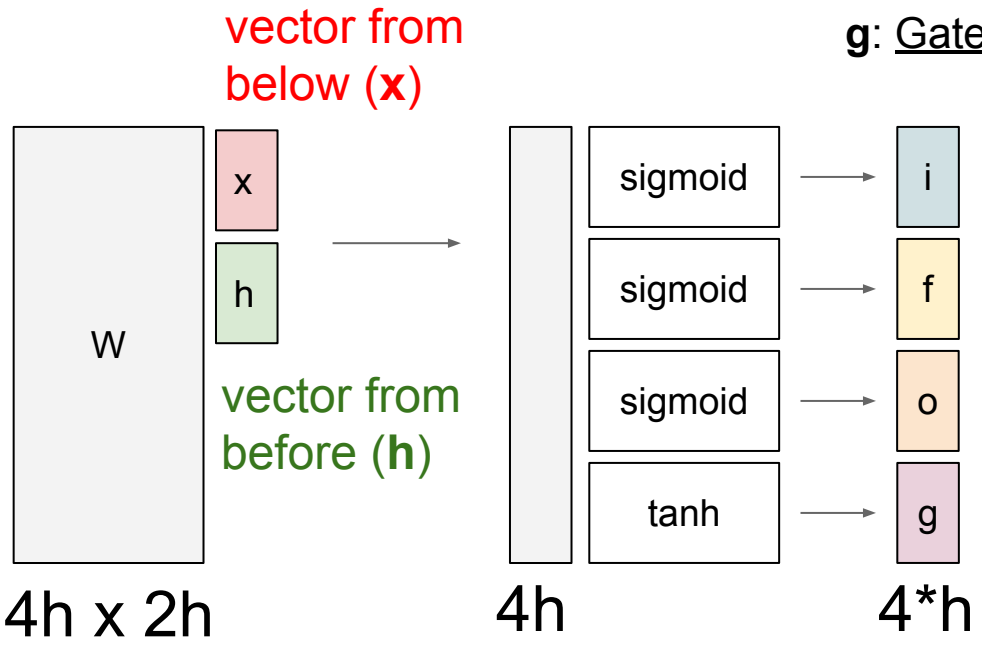
Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

i: Input gate, whether to write to cell

f: Forget gate, Whether to erase cell

g: Gate gate (?), How much to write to cell



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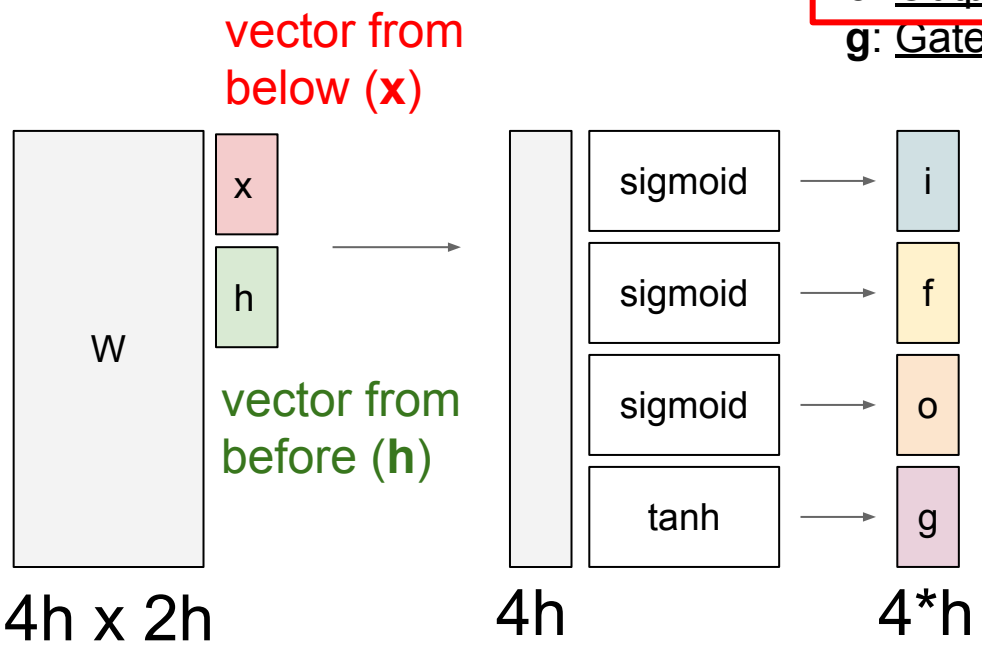
Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]

i: Input gate, whether to write to cell
f: Forget gate, Whether to erase cell
o: Output gate, How much to reveal cell
g: Gate gate (?), How much to write to cell



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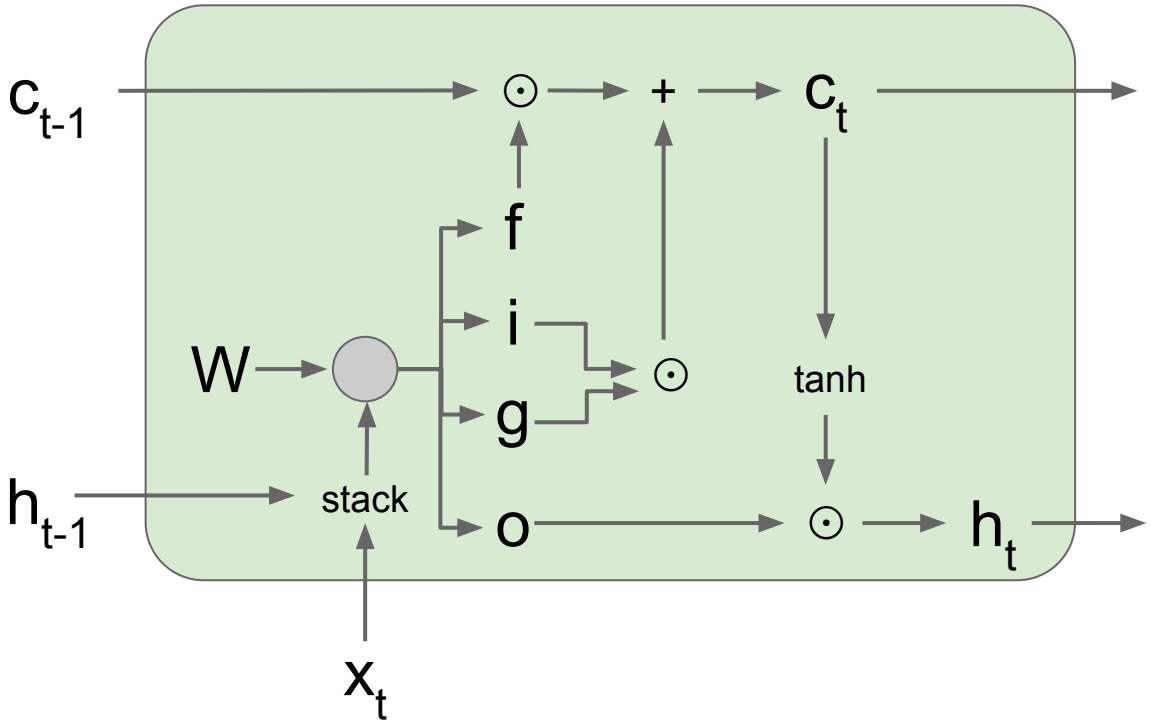
Long Short Term Memory (LSTM)

[Hochreiter et al., 1997]



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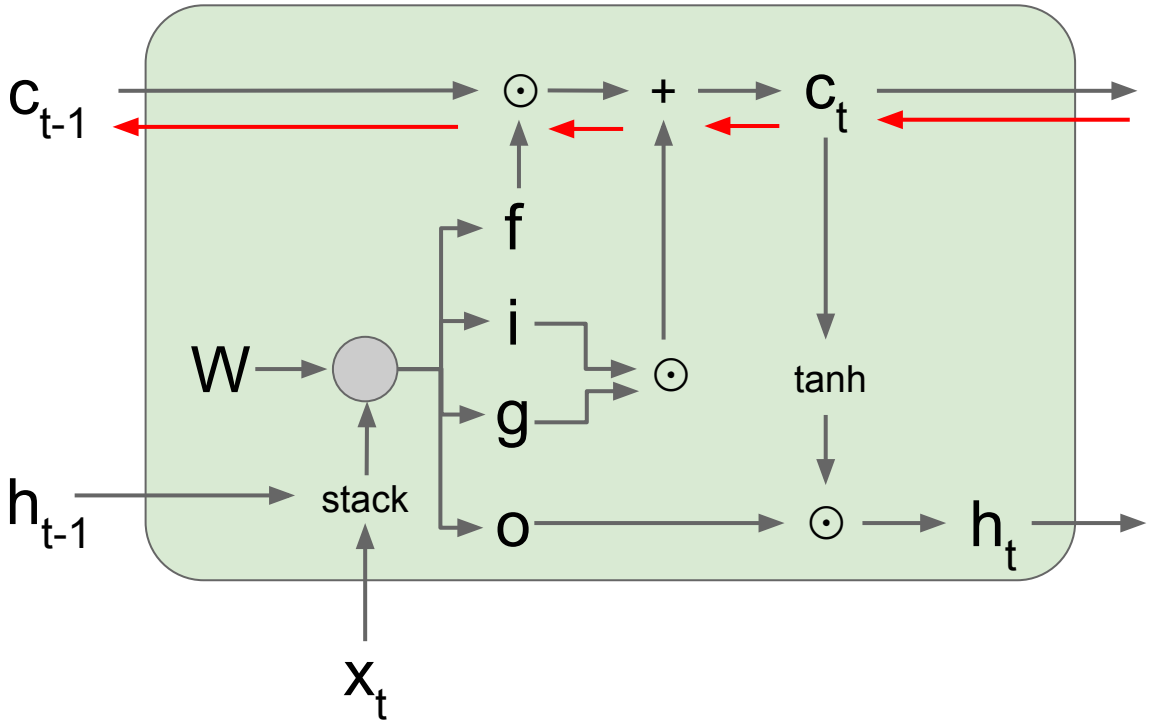
Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]



Backpropagation from c_t to c_{t-1} only elementwise multiplication by f, no matrix multiply by W

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

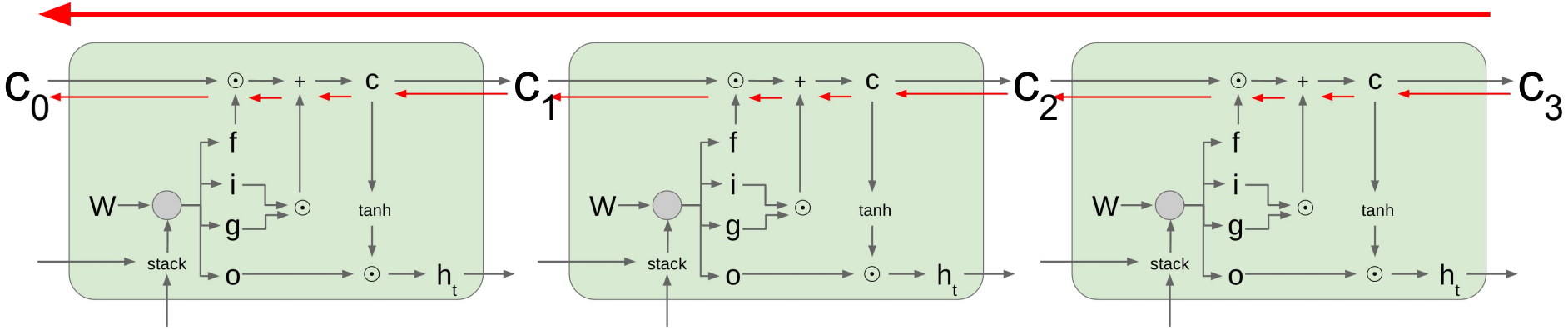
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Long Short Term Memory (LSTM): Gradient Flow

[Hochreiter et al., 1997]

Uninterrupted gradient flow!



Notice that the gradient contains the **f** gate's vector of activations

- allows better control of gradients values, using suitable parameter updates of the forget gate.

Also notice that are added through the **f, i, g,** and **o** gates

- better balancing of gradient values

GRU

Упрощенная версия LSTM

GRU (Gated Recurrent Unit) — это еще один тип рекуррентной нейронной сети (RNN), который был предложен в 2014 году для улучшения обработки последовательных данных. GRU схожа с LSTM, но имеет более простую архитектуру, что делает её быстрее и проще в обучении, при этом сохраняя способность моделировать долгосрочные зависимости.
Основные характеристики GRU

Гейты:

В GRU используются два типа гейтов:

Гейт обновления (Update Gate): определяет, какую информацию из предыдущего состояния следует сохранить.

Гейт сброса (Reset Gate): решает, какую информацию из предыдущего состояния следует забыть.

Единое состояние:

В отличие от LSTM, где есть отдельные состояния ячейки и скрытого состояния, в GRU используется только одно состояние, что упрощает архитектуру.

Простота:

GRU имеет меньше параметров, чем LSTM, что может ускорить процесс обучения и снизить вероятность переобучения.

Update gate

Reset gate

$$\boldsymbol{u}^{(t)} = \sigma\left(\boldsymbol{W}_u \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_u \boldsymbol{x}^{(t)} + \boldsymbol{b}_u\right)$$

$$\boldsymbol{r}^{(t)} = \sigma\left(\boldsymbol{W}_r \boldsymbol{h}^{(t-1)} + \boldsymbol{U}_r \boldsymbol{x}^{(t)} + \boldsymbol{b}_r\right)$$

$$\tilde{\boldsymbol{h}}^{(t)} = \tanh\left(\boldsymbol{W}_h (\boldsymbol{r}^{(t)} \circ \boldsymbol{h}^{(t-1)}) + \boldsymbol{U}_h \boldsymbol{x}^{(t)} + \boldsymbol{b}_h\right)$$

$$\boldsymbol{h}^{(t)} = (1 - \boldsymbol{u}^{(t)}) \circ \boldsymbol{h}^{(t-1)} + \boldsymbol{u}^{(t)} \circ \tilde{\boldsymbol{h}}^{(t)}$$

Image credit

Рекуррентные нейросети (RNN)

GRU и LSTM - уменьшают проблему vanishing gradients

Преодоление проблемы исчезающих градиентов: LSTM сохраняют информацию на более длительные периоды, что помогает обучать модели на длинных последовательностях.

Recurrence for Vision

- LSTM wer a good default choice until this year
- Use variants like GRU if you want faster compute and less parameters
- Use transformers (next lecture) as they are dominating NLP models
  - almost everyday there is a new vision transformer model

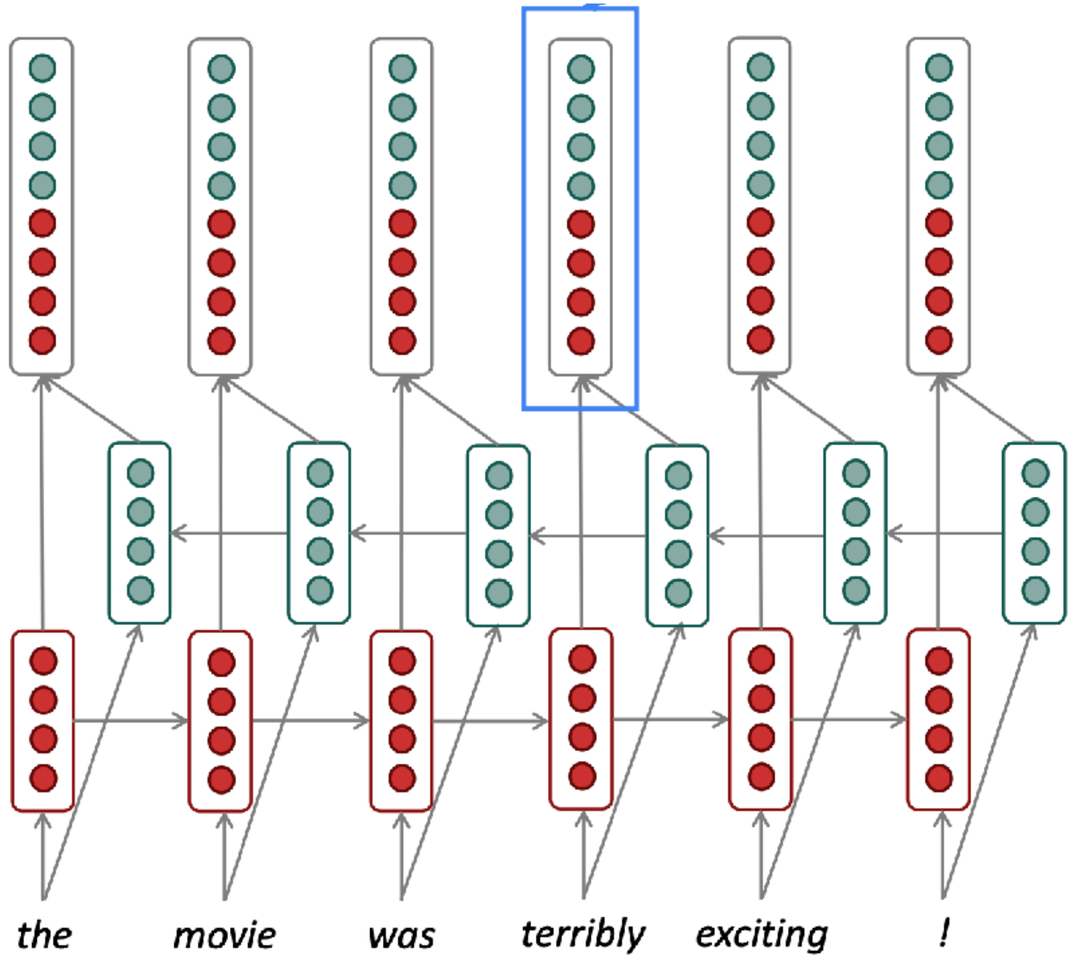
Su et al. "Vl-bert: Pre-training of generic visual-linguistic representations." ICLR 2020
Lu et al. "Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks." NeurIPS 2019
Li et al. "Visualbert: A simple and performant baseline for vision and language." *arXiv* 2019

Рекуррентные нейросети (RNN)

Улучшения: bidirectional RNN (если порядок не важен)

Обрабатываем последовательные данные в обоих направлениях: от начала к концу и от конца к началу. Это достигается за счет использования двух отдельных RNN, которые работают параллельно. Один из них обрабатывает последовательность в прямом направлении, а другой — в обратном.

Матрицы весов абсолютно независимы, между ними нет взаимодействия, просто для каждого элемента последовательно- сти получатся два состояния: слева направо и справа налево.



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Рекуррентные нейросети (RNN)

Улучшения: stacked RNN

Каждый слой принимает на вход выход предыдущего слоя, что позволяет модели извлекать более сложные и абстрактные представления данных.

Увеличение числа слоев может привести к проблемам с переобучением и затруднениям в обучении, таким как исчезновение градиента. Для решения этих проблем могут использоваться различные техники, такие как регуляризация, использование LSTM (Long Short-Term Memory) или GRU (Gated Recurrent Unit) вместо стандартных RNN, а также методы нормализации.

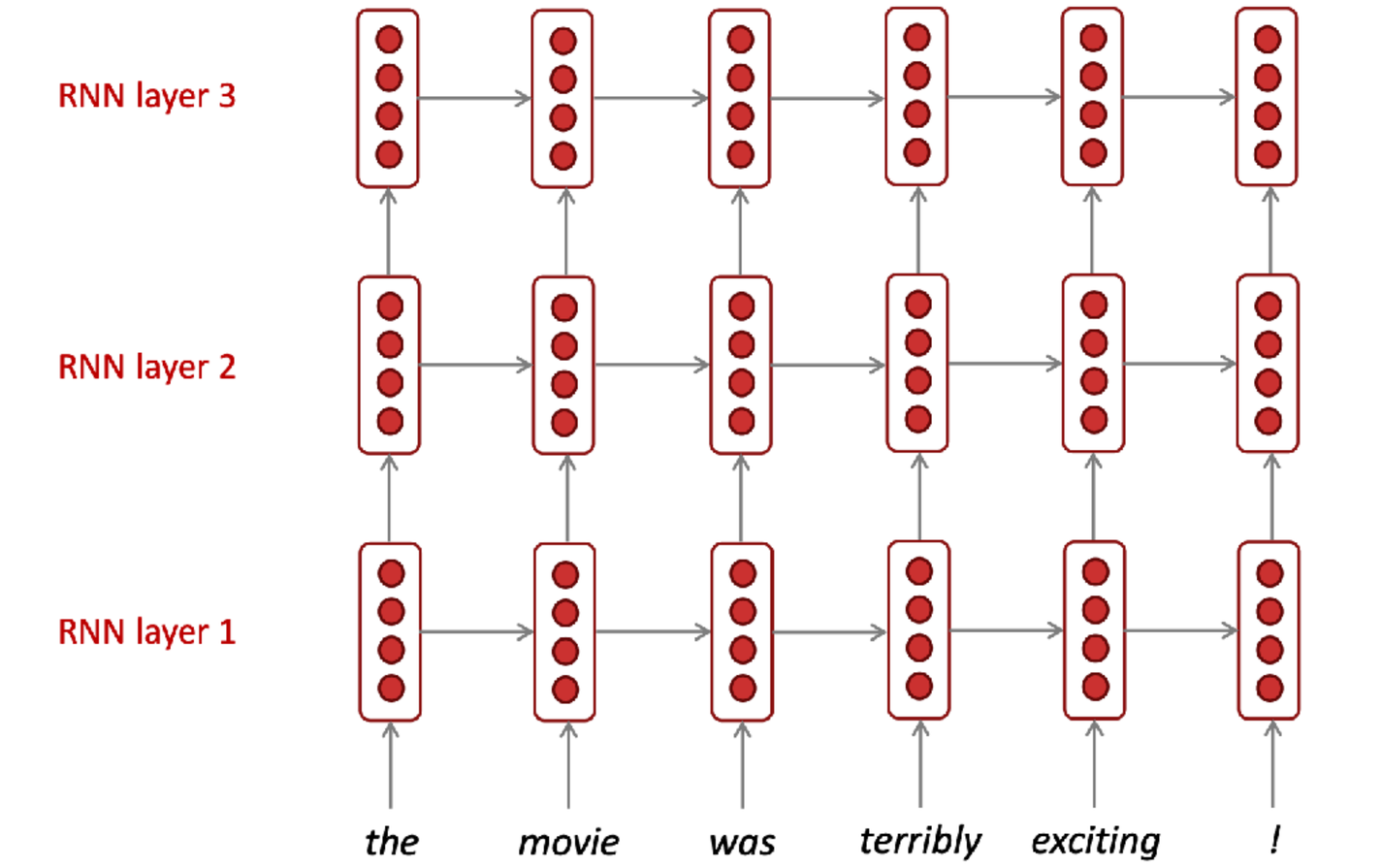


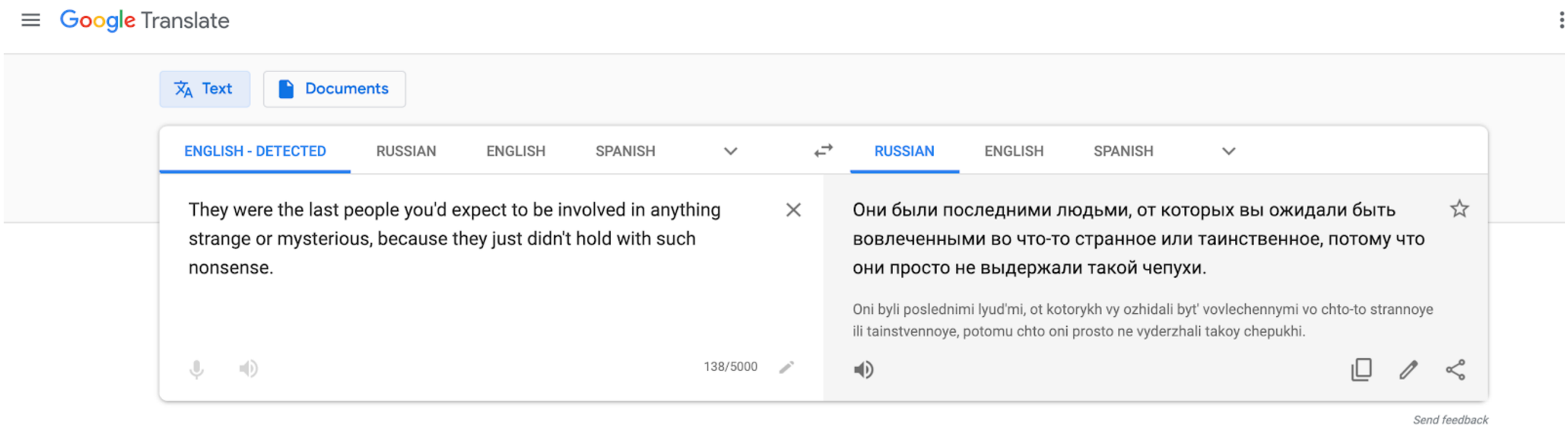
Image credit

Summary

- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don’t work very well
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)
- Better/simpler architectures are a hot topic of current research, as well as new paradigms for reasoning over sequences
- Better understanding (both theoretical and empirical) is needed.

Sequence-to-sequence model

Приложения: перевод



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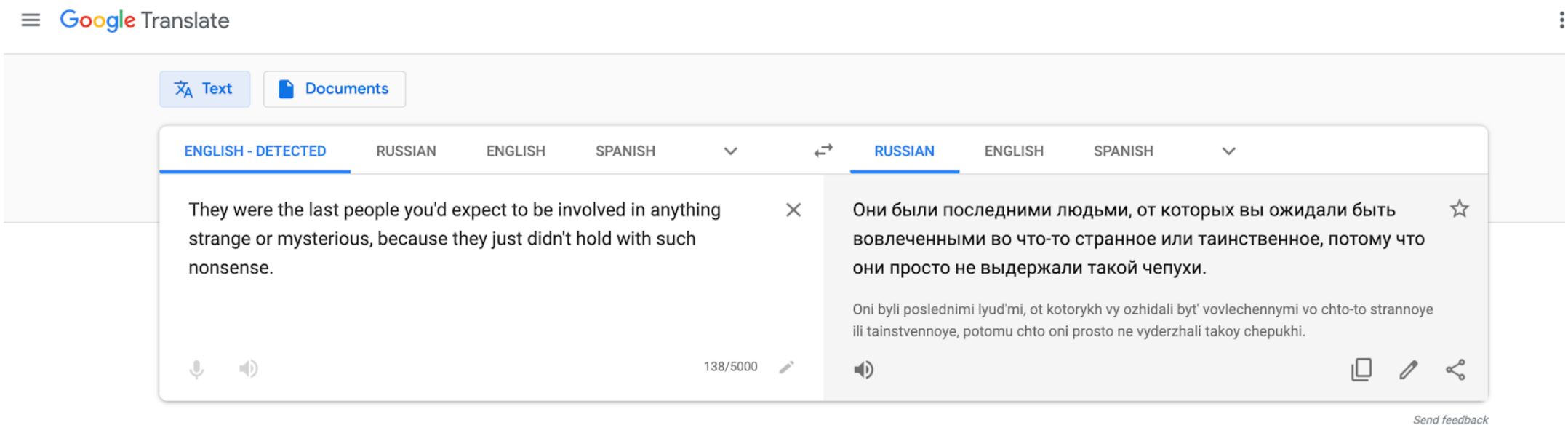


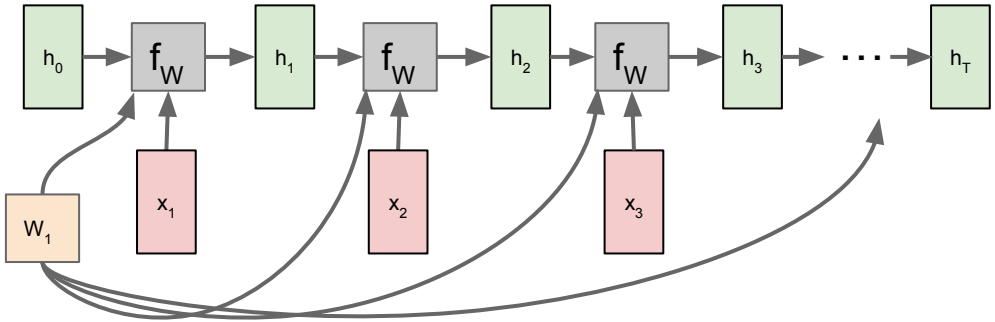
Авторегрессионная модель $p(y \mid x) = = \prod_{i=1}^{n} p(y_i \mid y_1, \ldots, y_{i-1}, x)$

x - текст на исходном языке (source)

y - перевод текста на другой язык (target)

Sequence to Sequence: Many-to-one + one-to-many

Many to one: Encode input sequence in a single vector

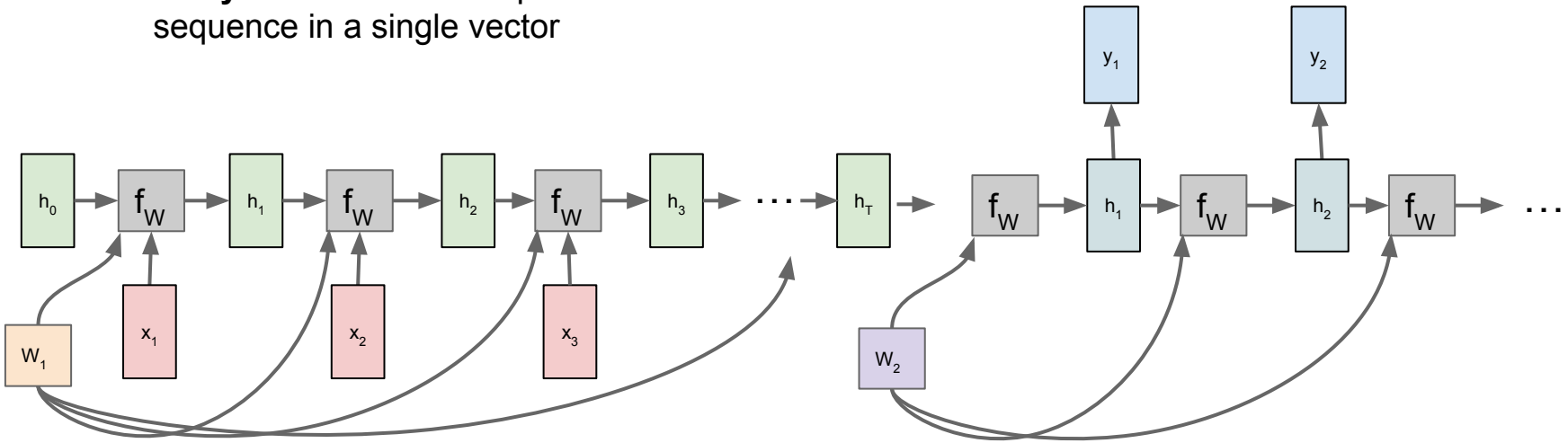


Sutskever et al, “Sequence to Sequence Learning with Neural Networks”, NIPS 2014

Sequence to Sequence: Many-to-one + one-to-many

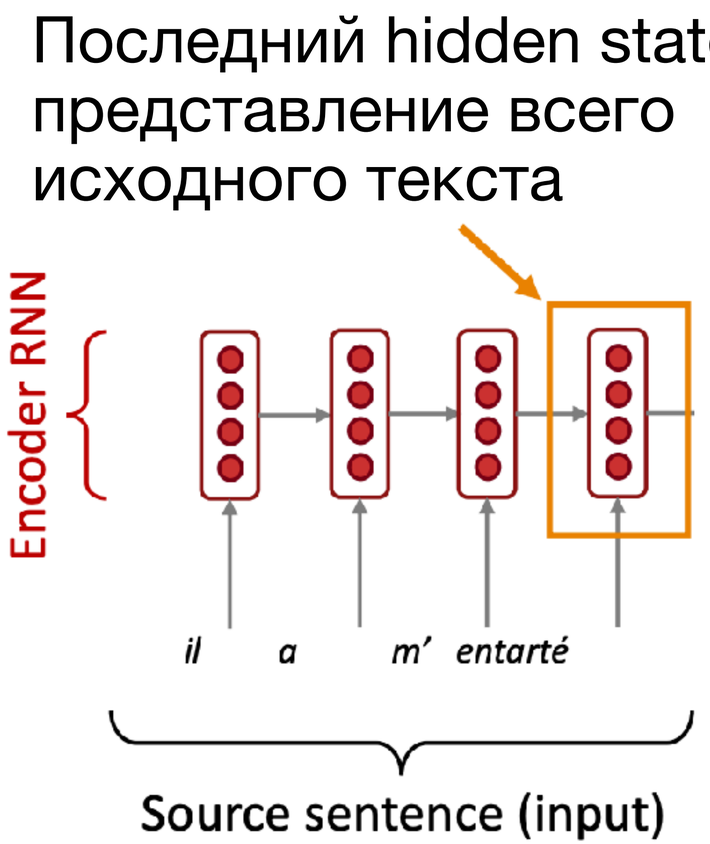
Many to one: Encode input sequence in a single vector

One to many: Produce output sequence from single input vector



Sutskever et al, “Sequence to Sequence Learning with Neural Networks”, NIPS 2014

Sequence-to-sequence model



Sequence-to-Sequence (Seq2Seq) Model — это тип нейронной сети, который предназначен для обработки и преобразования последовательностей данных одной длины в последовательности другой длины. Эта модель широко используется в задачах, связанных с обработкой естественного языка, таких как машинный перевод, генерация текста, подведение итогов и многие другие.
Основные компоненты Seq2Seq

Энкодер (Encoder):

Энкодер принимает входную последовательность и преобразует её в фиксированное представление (контекстный вектор). Обычно это RNN, LSTM или GRU.

Каждый элемент входной последовательности обрабатывается, и в конце энкодер выдает вектор, который представляет всю последовательность.

Декодер (Decoder):

Декодер принимает контекстный вектор от энкодера и генерирует выходную последовательность.

Он также может быть реализован с помощью RNN, LSTM или GRU.

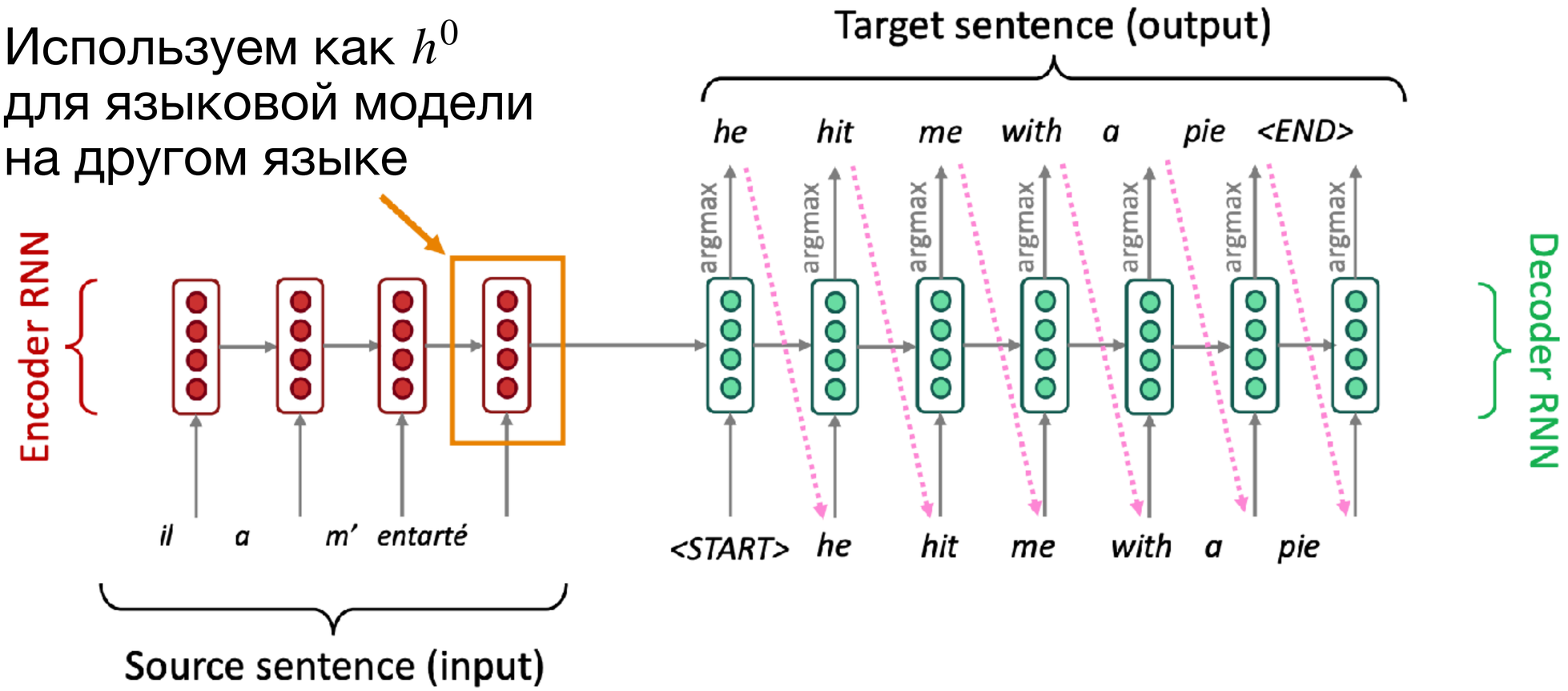
Важно, чтобы декодер имел возможность получать предсказанные элементы в качестве входа для генерации следующего элемента (это называется teacher forcing).

Контекстный вектор:

Этот вектор, созданный энкодером, содержит всю информацию о входной последовательности, и декодер использует его для генерации выходной последовательности.

Image credit

Используем как h^0 для языковой модели на другом языке



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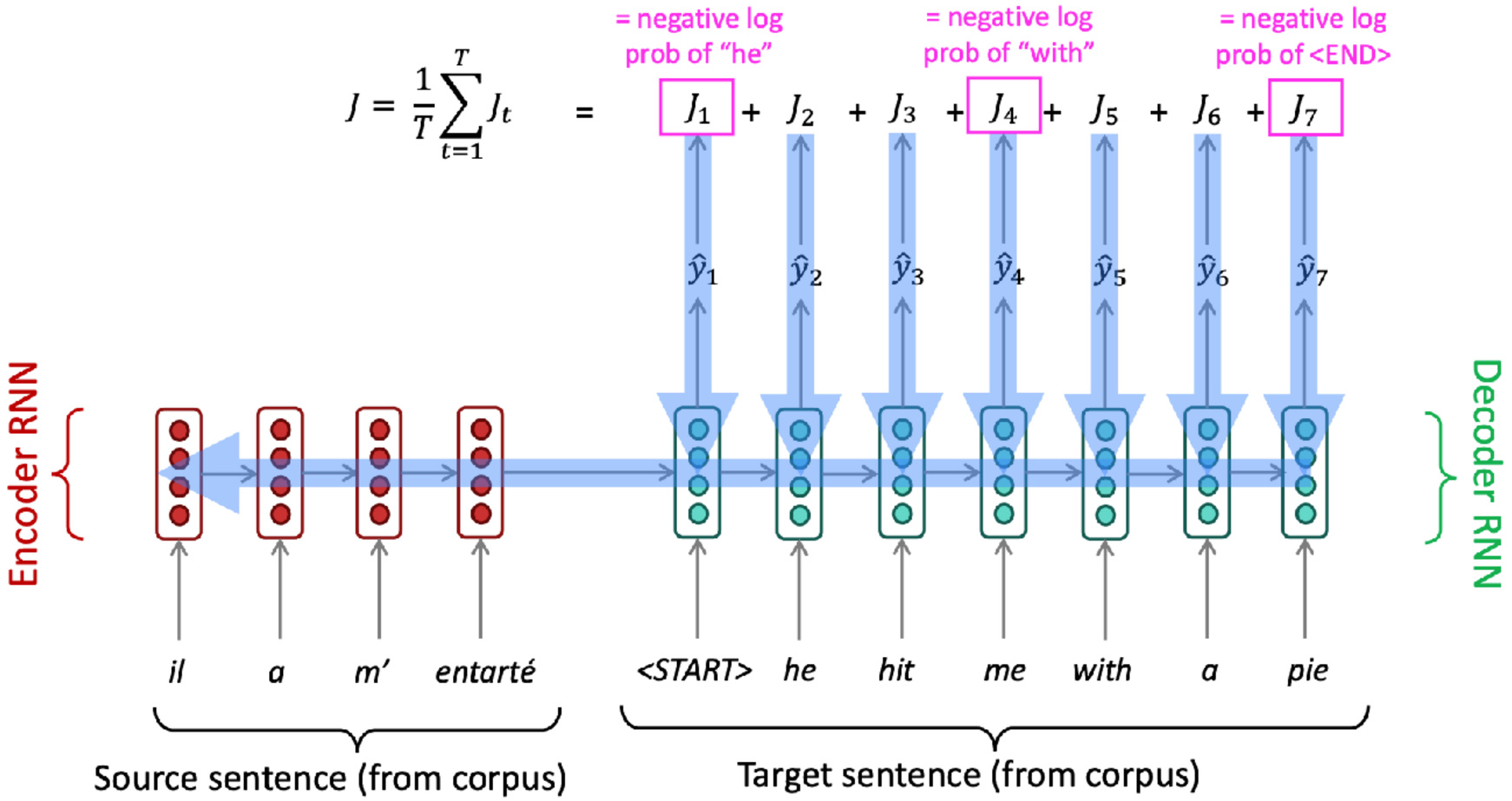
Sequence-to-sequence model

Обучение: нужен параллельный корпус



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Sequence-to-sequence model

Генерация:

- greedy (берем argmax)
- сэмплирование
- beam search

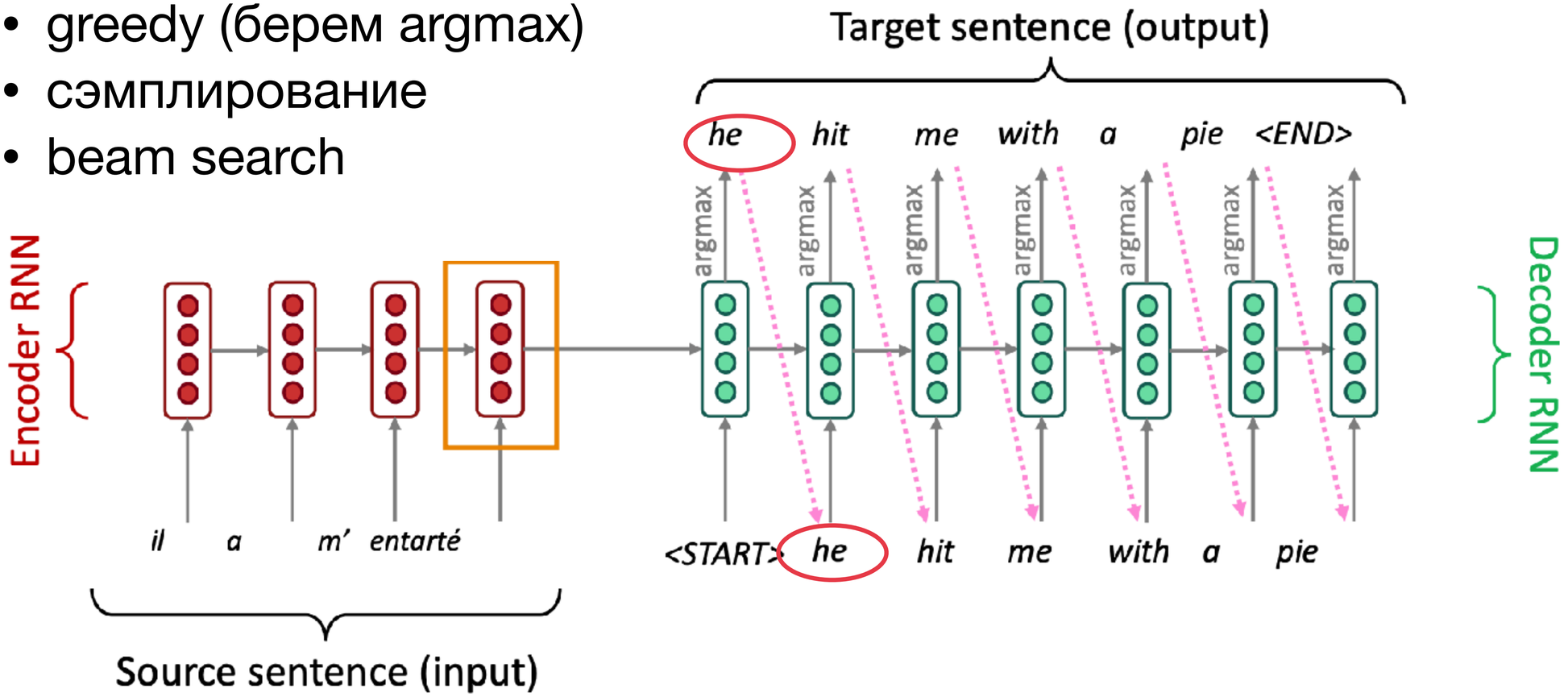
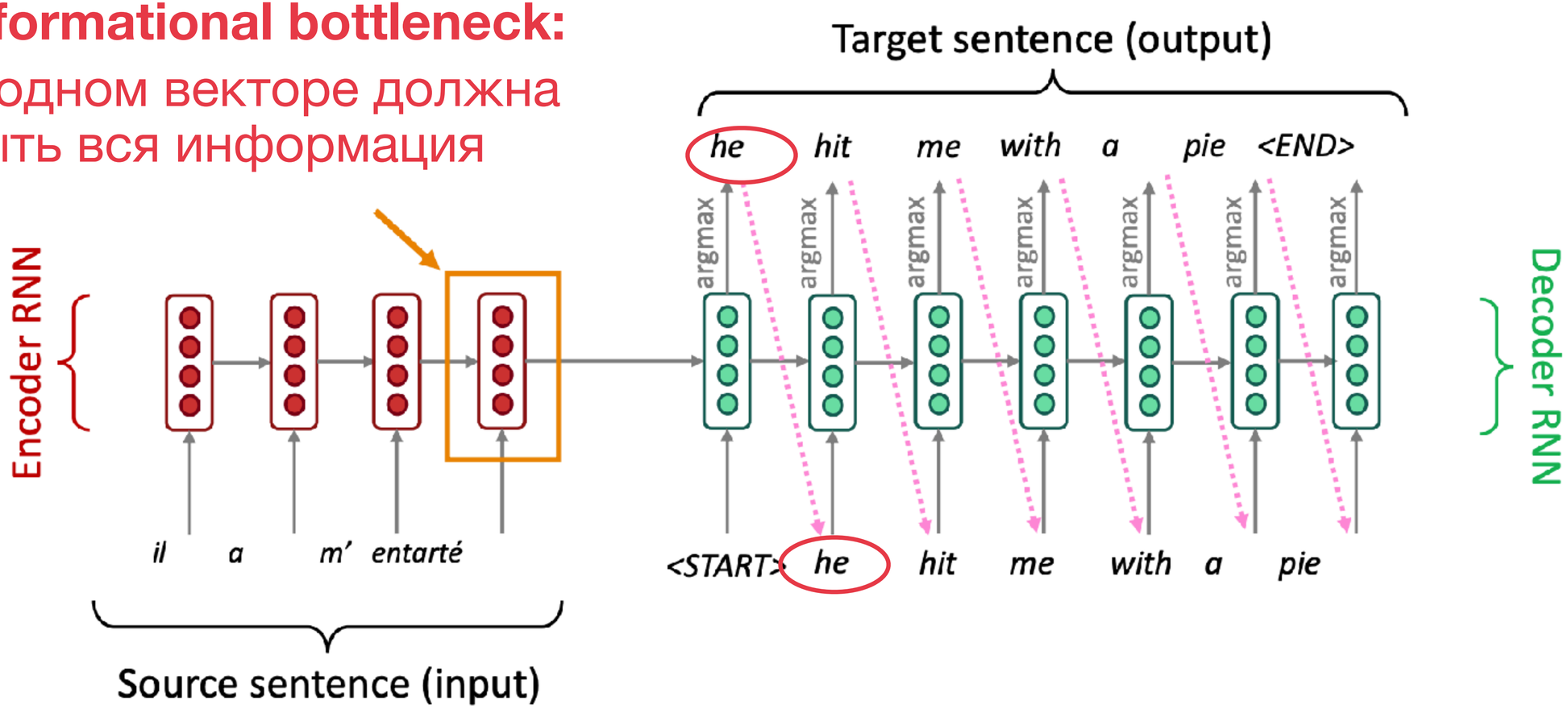


Image credit

Sequence-to-sequence model

Informational bottleneck:

В одном векторе должна быть вся информация



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