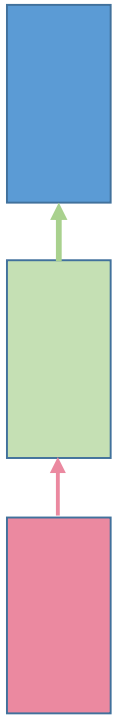
Рекуррентные нейронные сети

Как предсказать следующее слово?

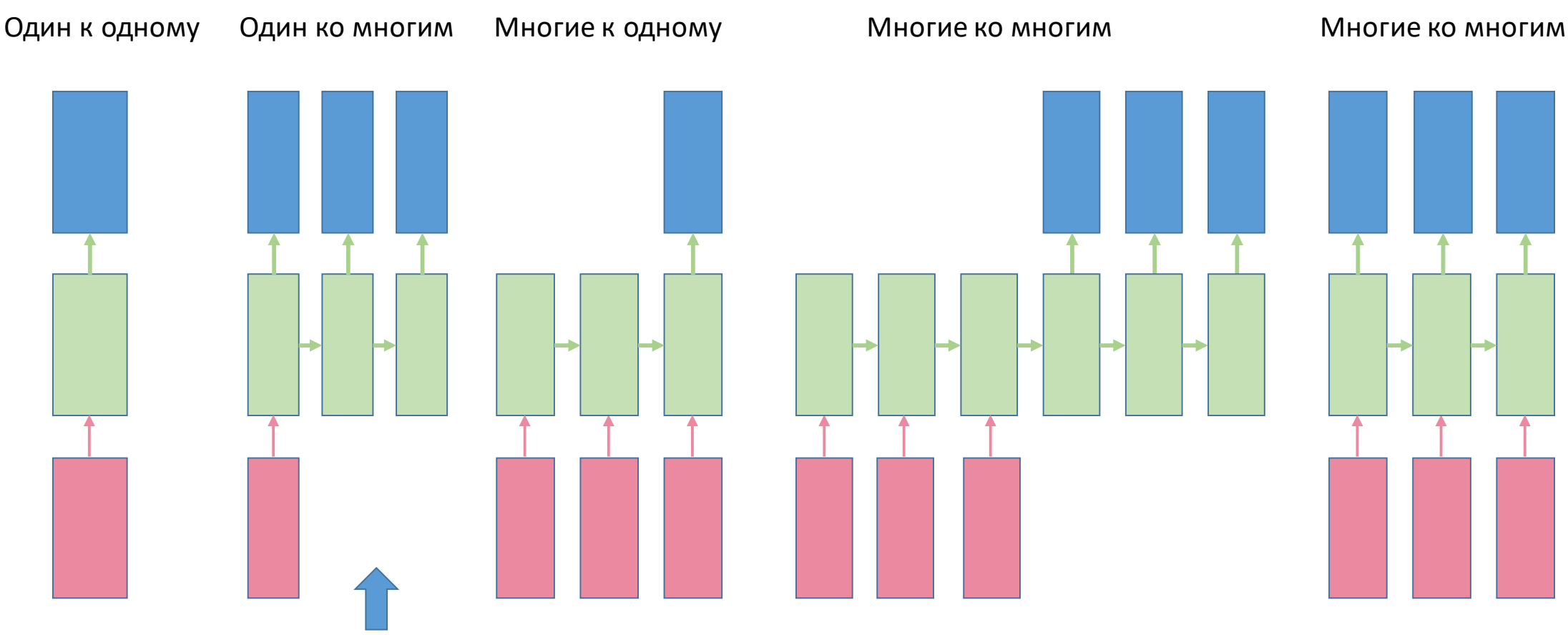
- Посмотреть на предыдущее слово?
- Посмотреть на предыдущие 3 слова?

Сеть прямого распространения

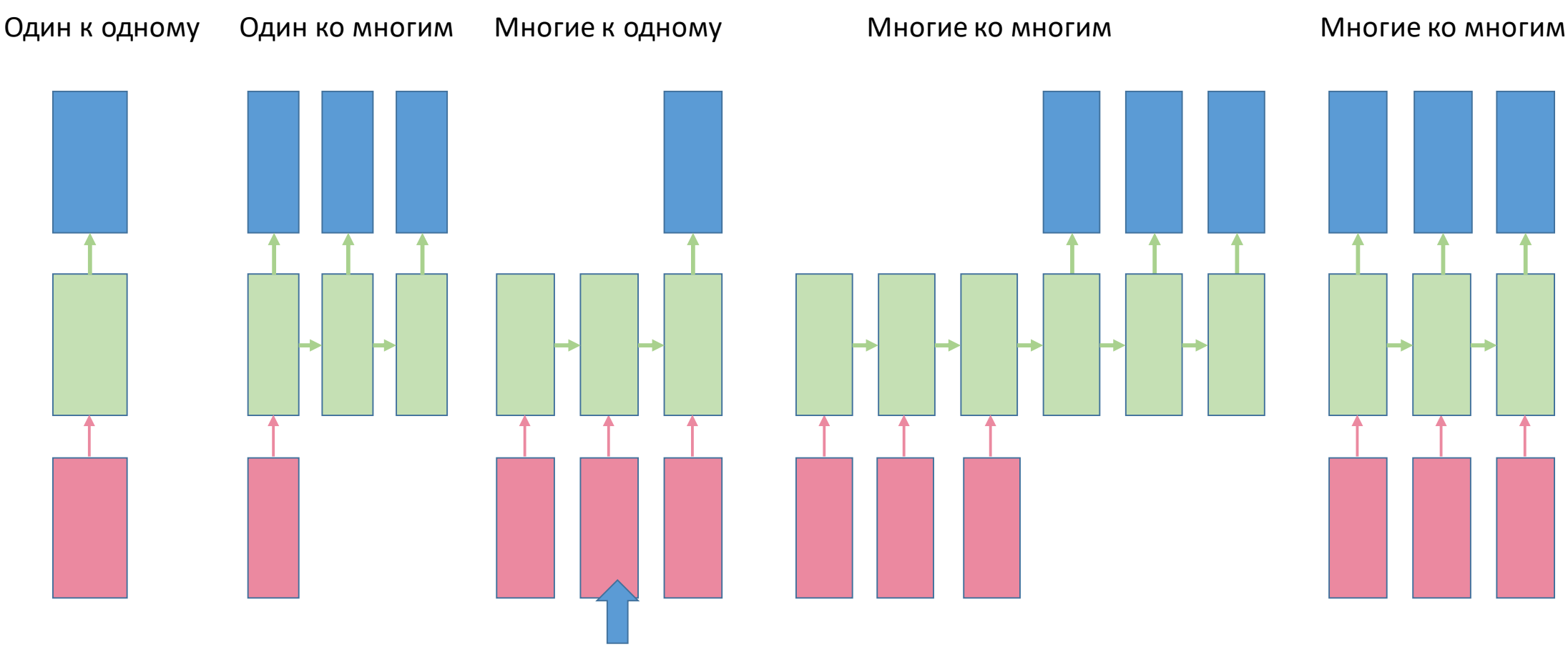
Один к одному



Рекуррентная нейросеть



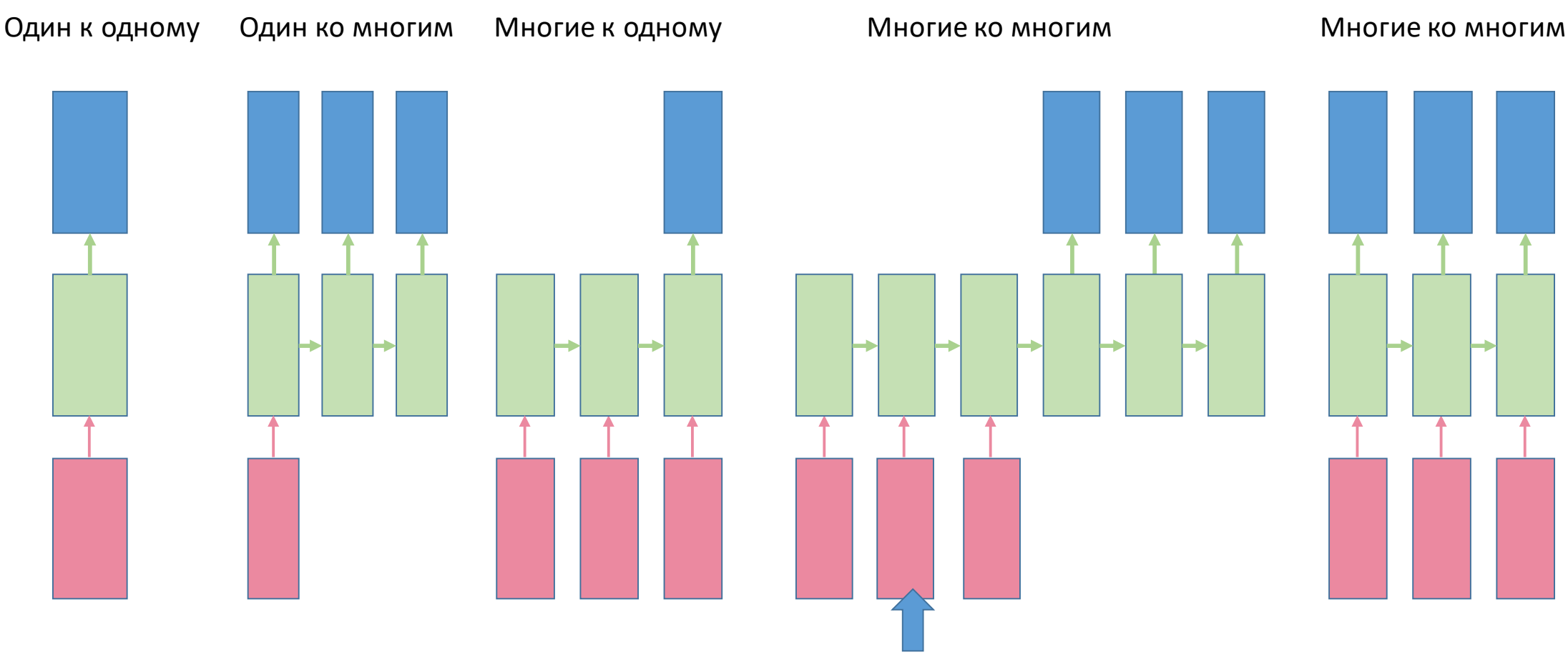
Рекуррентная нейросеть



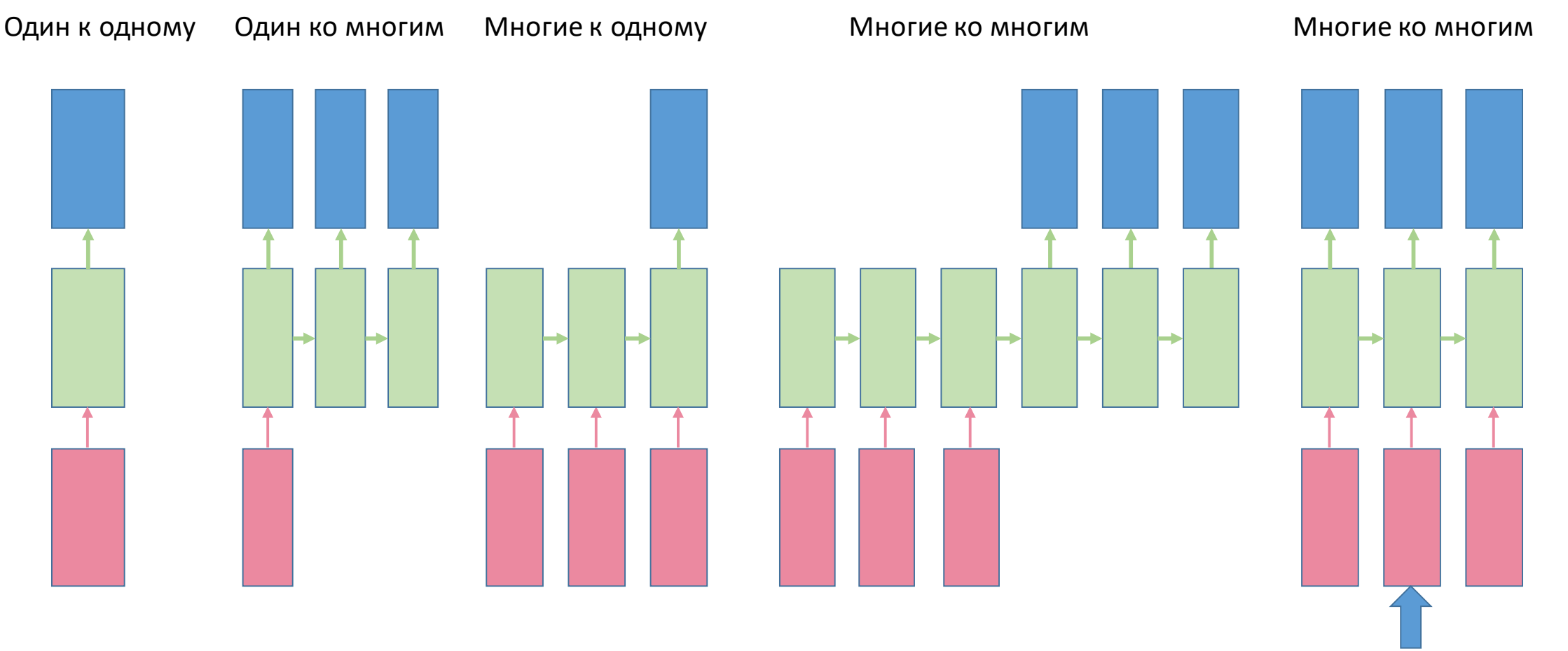
Анализ тональности текста

Вход – текст. Выход класс тональности

Рекуррентная нейросеть



Рекуррентная нейросеть



Рекуррентная формула

Сеть подает на вход в момент времени *t* выход *t-1*

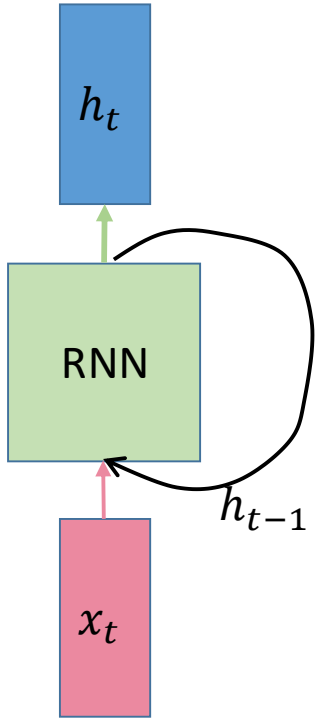
$$h_t = f_W(h_{t-1}, x_t)$$

Новое состояние

Старое состояние

Вход на шаге t

Функция с параметрами W



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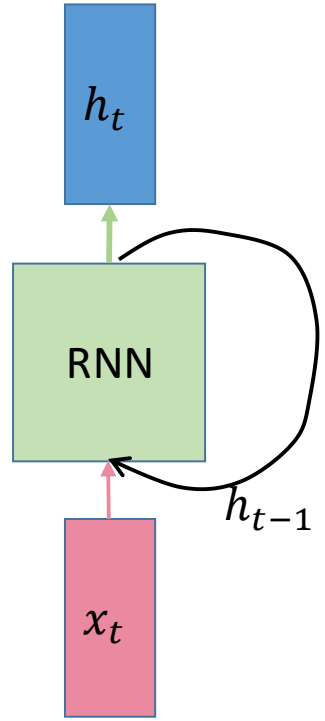


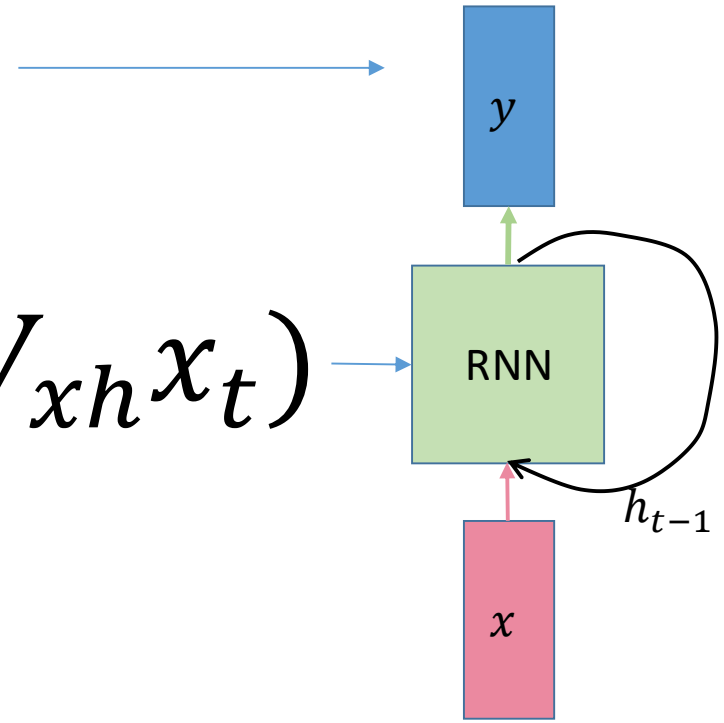
Для каждого момента времени используется одна функция и одна матрица весов

Базовая рекуррентная сеть

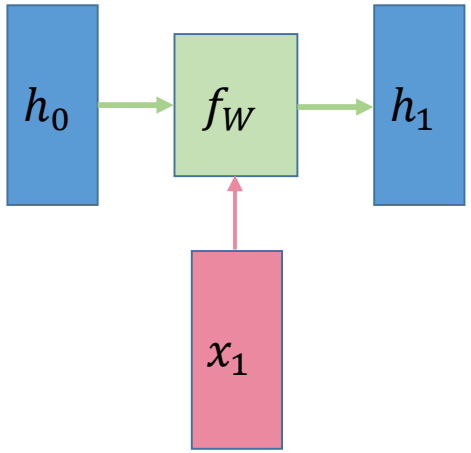
$$y_t = W_{hy}\, h_t$$

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

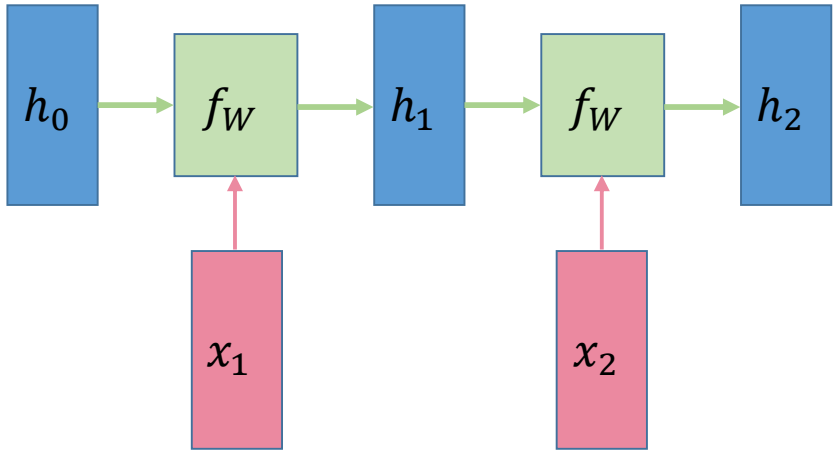
$$h_t = f_W\,(h_{t-1}, x_t)$$



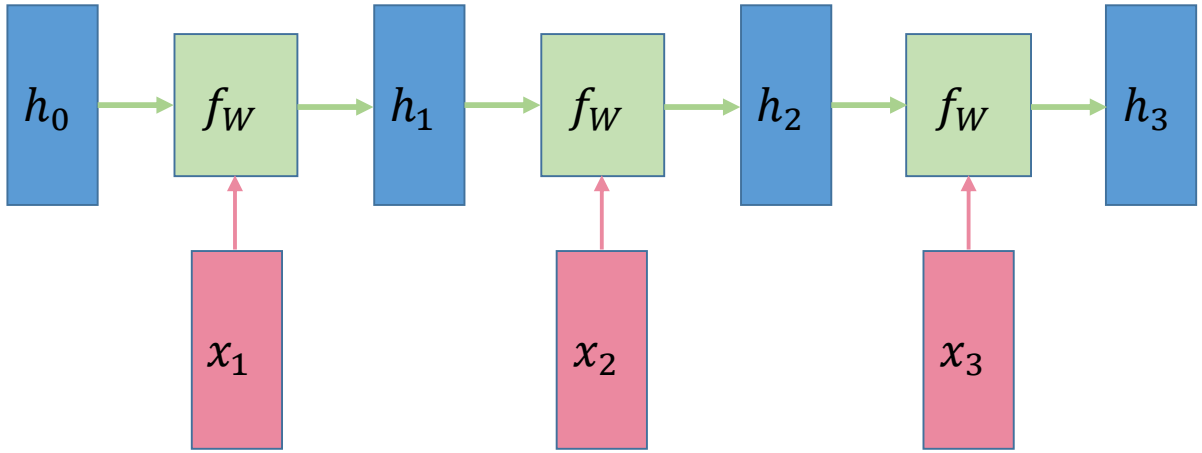
RNN вычислительный граф



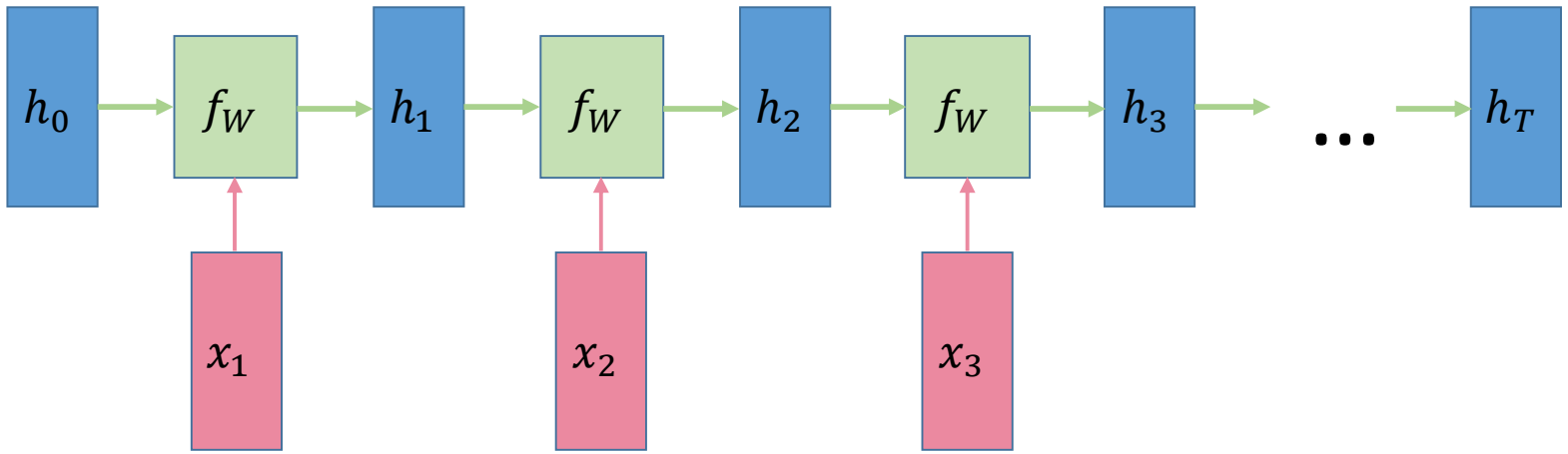
RNN вычислительный граф



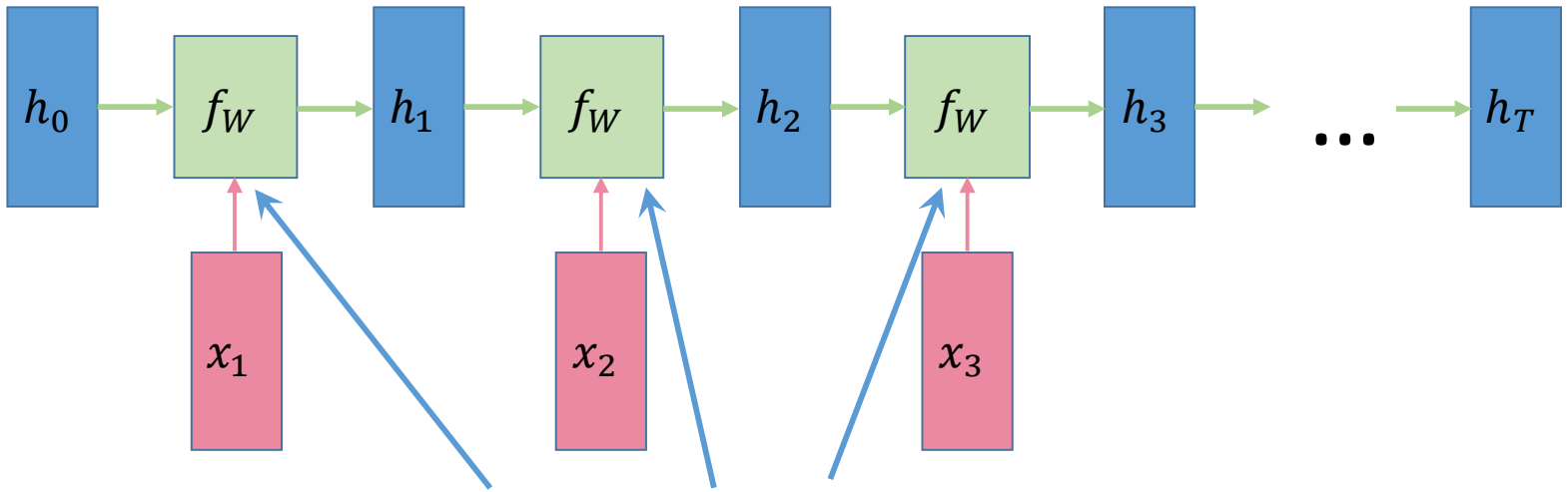
RNN вычислительный граф



RNN вычислительный граф

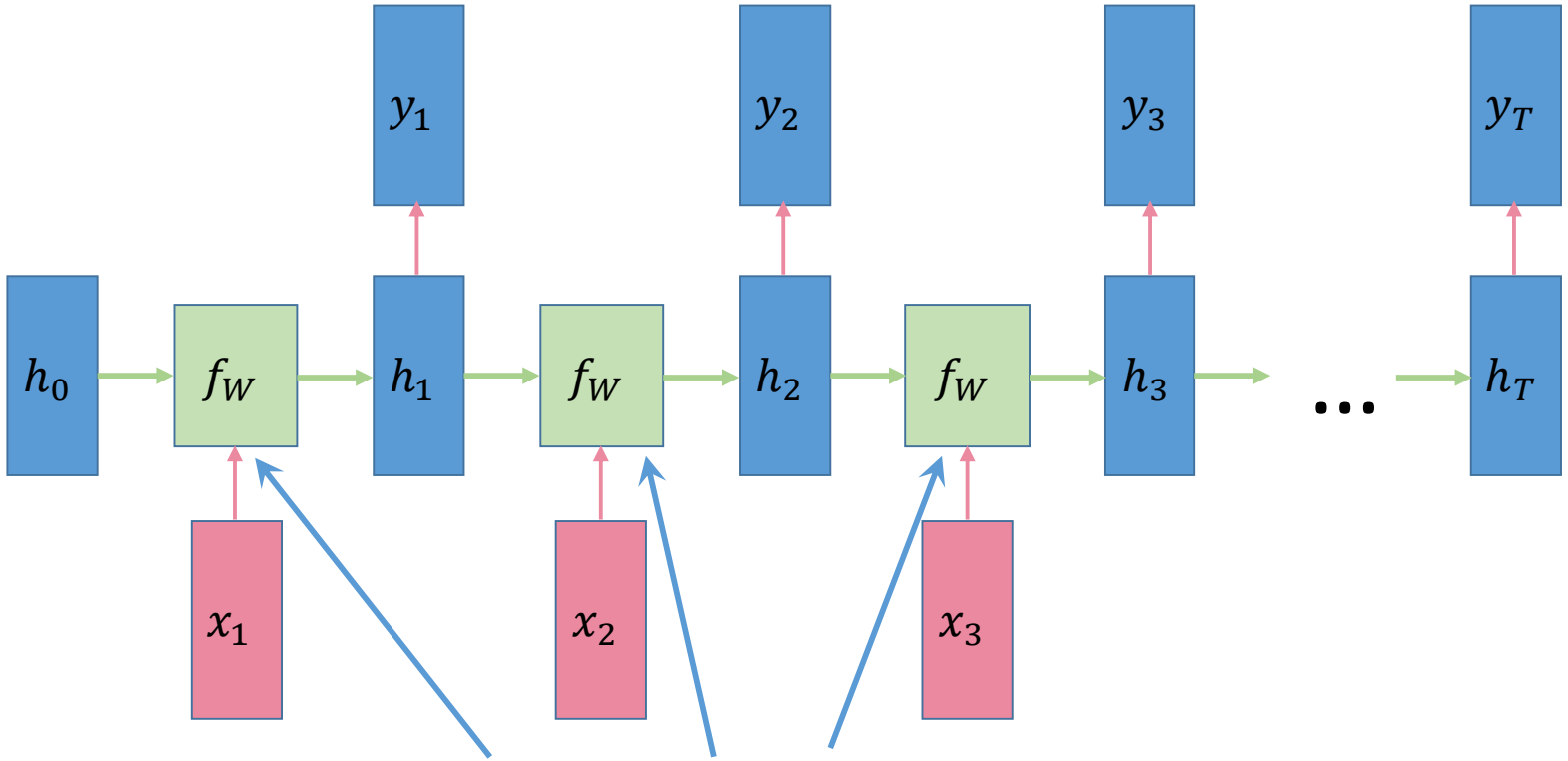


RNN вычислительный граф



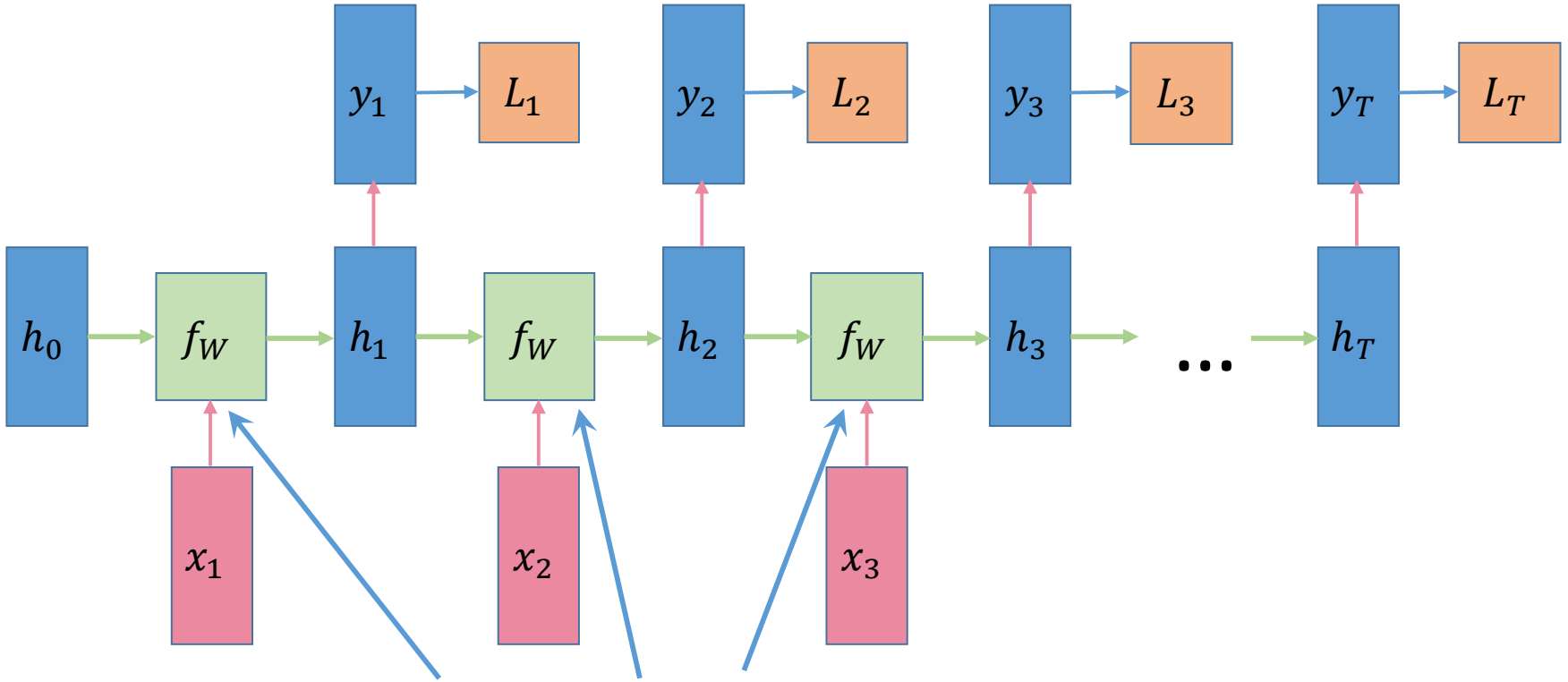
Одна матрица W на каждом шаге

Вычислительный граф. Многие ко многим



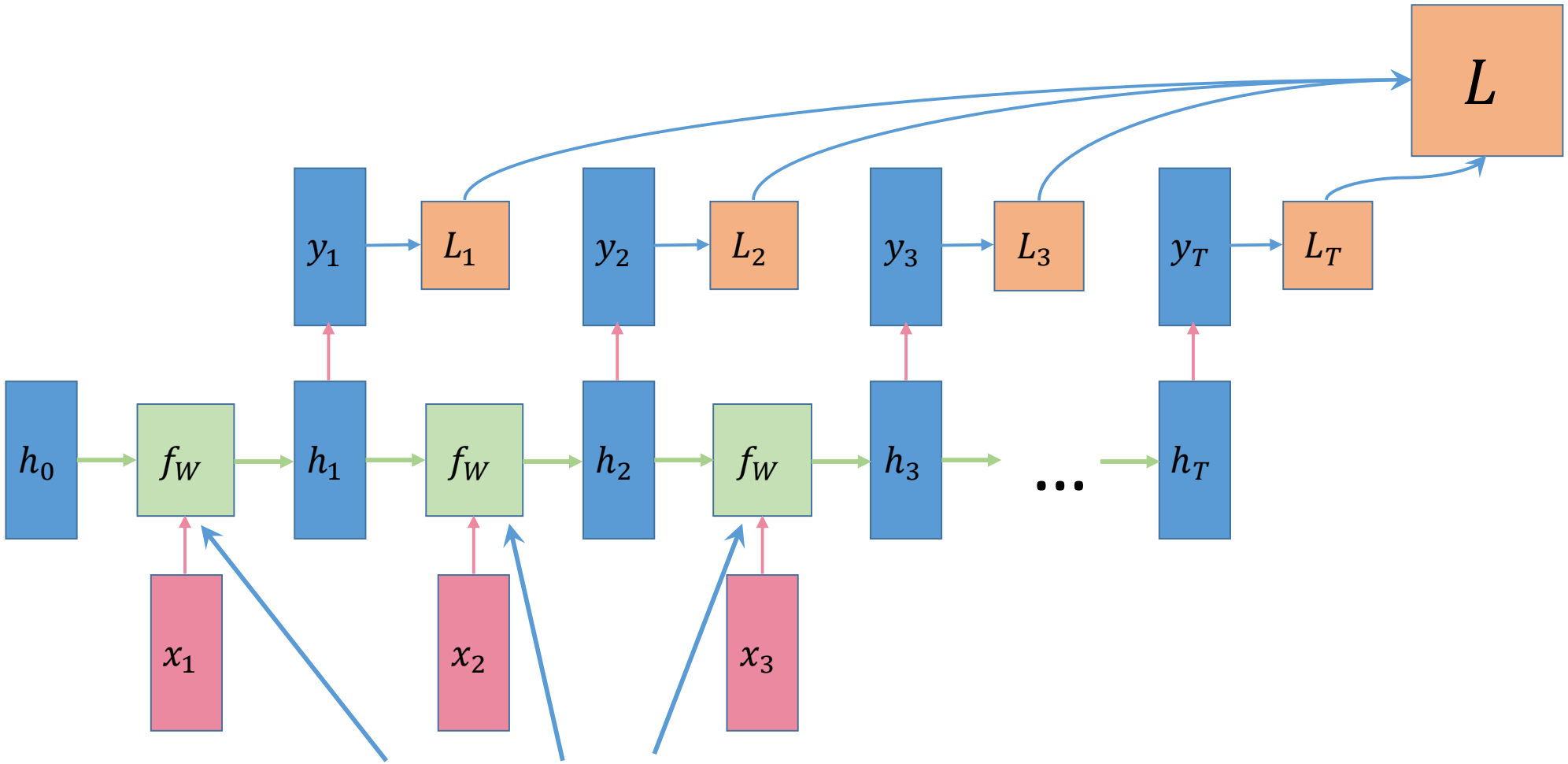
Одна матрица W на каждом шаге

Вычислительный граф. Многие ко многим



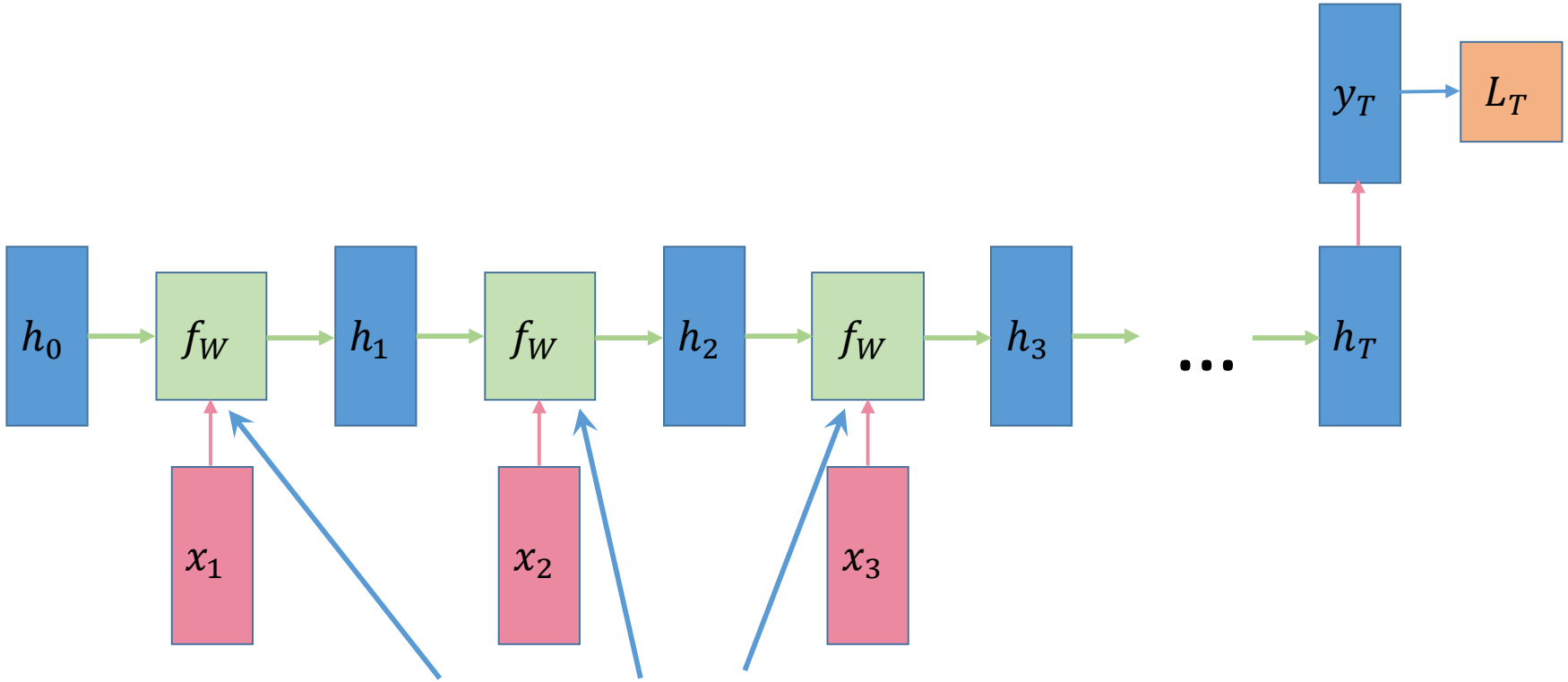
Одна матрица W на каждом шаге

Вычислительный граф. Многие ко многим



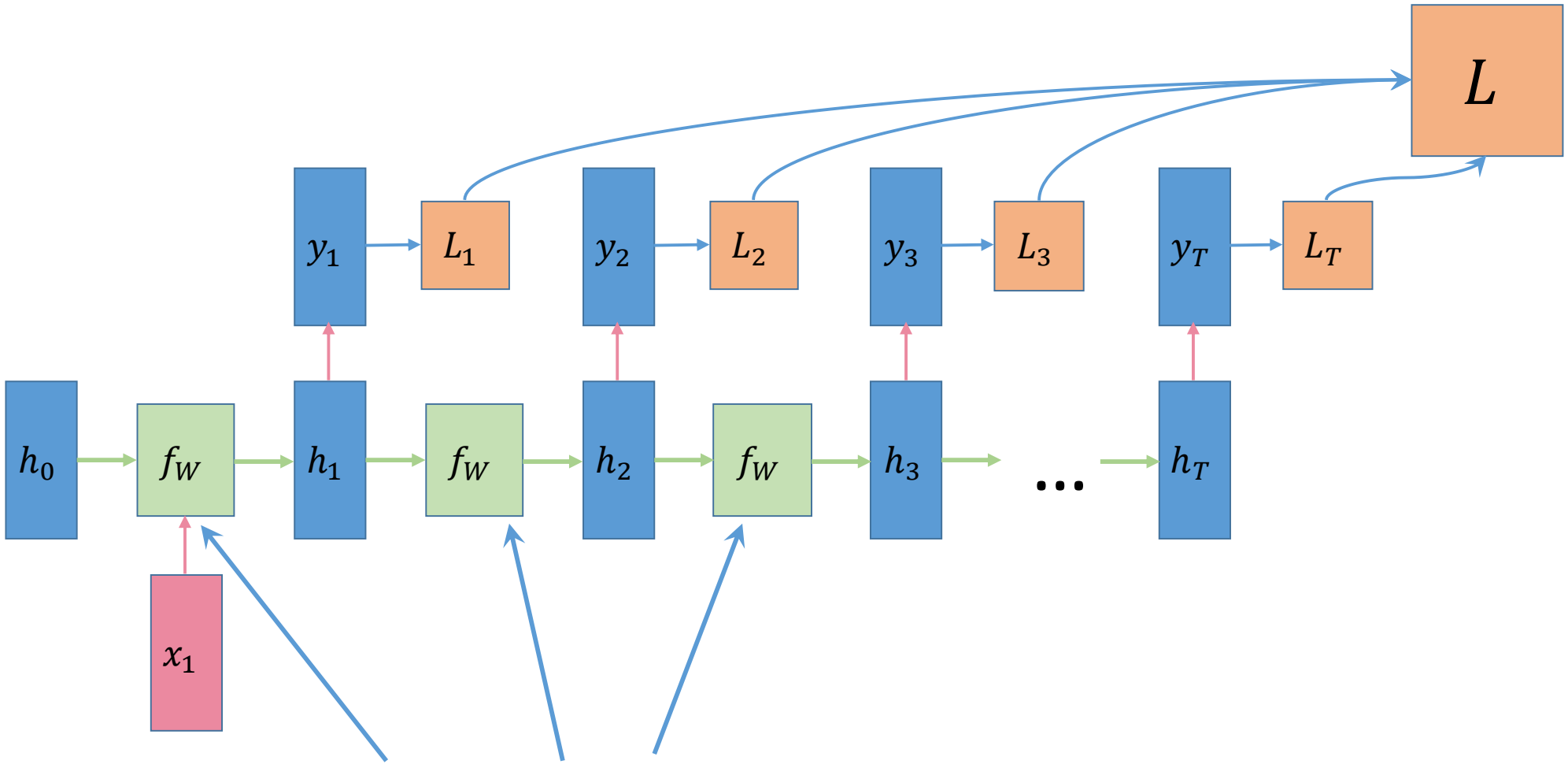
Одна матрица W на каждом шаге

Вычислительный граф. Многие к одному



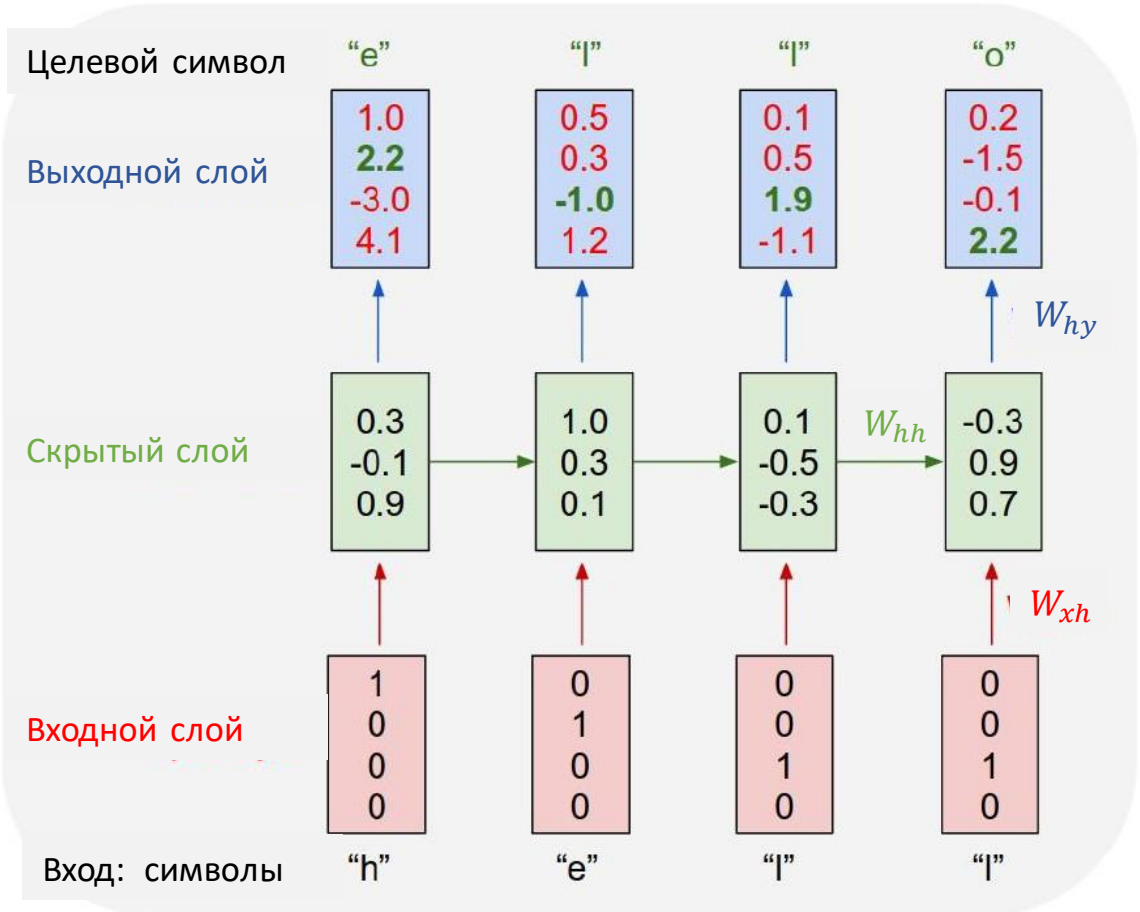
Одна матрица W на каждом шаге

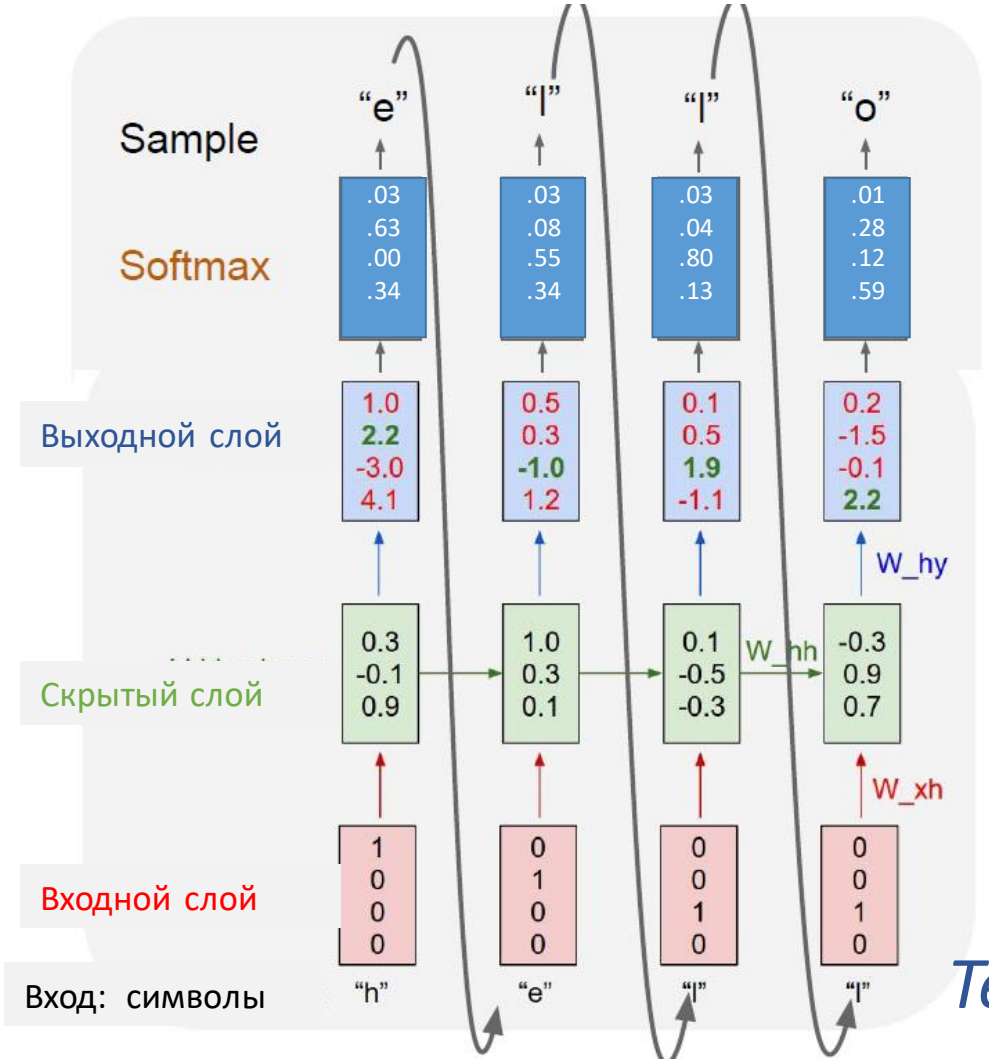
Вычислительный граф. Один ко многим



Одна матрица W на каждом шаге

Character-level. Языковая модель



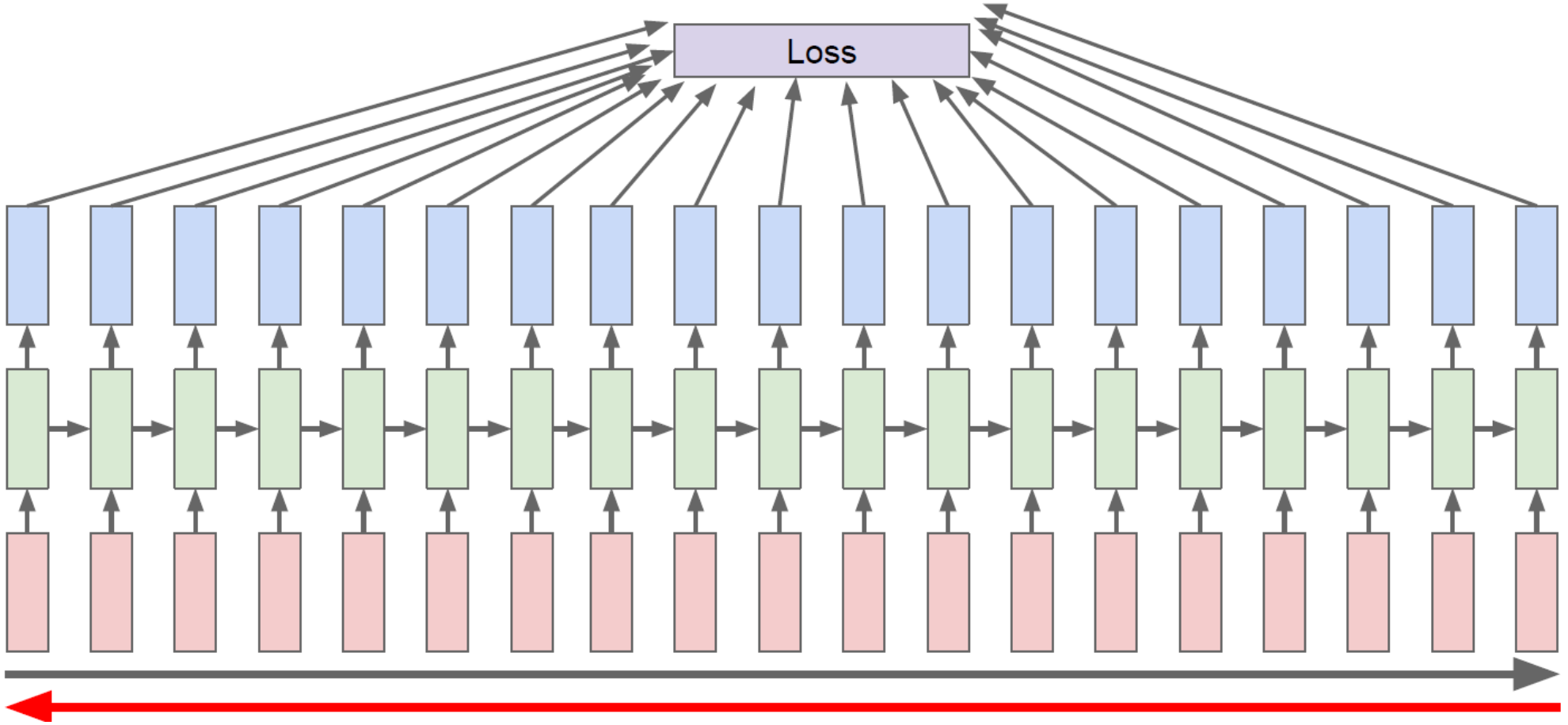


Train

Словарь: [h,e,l,o]

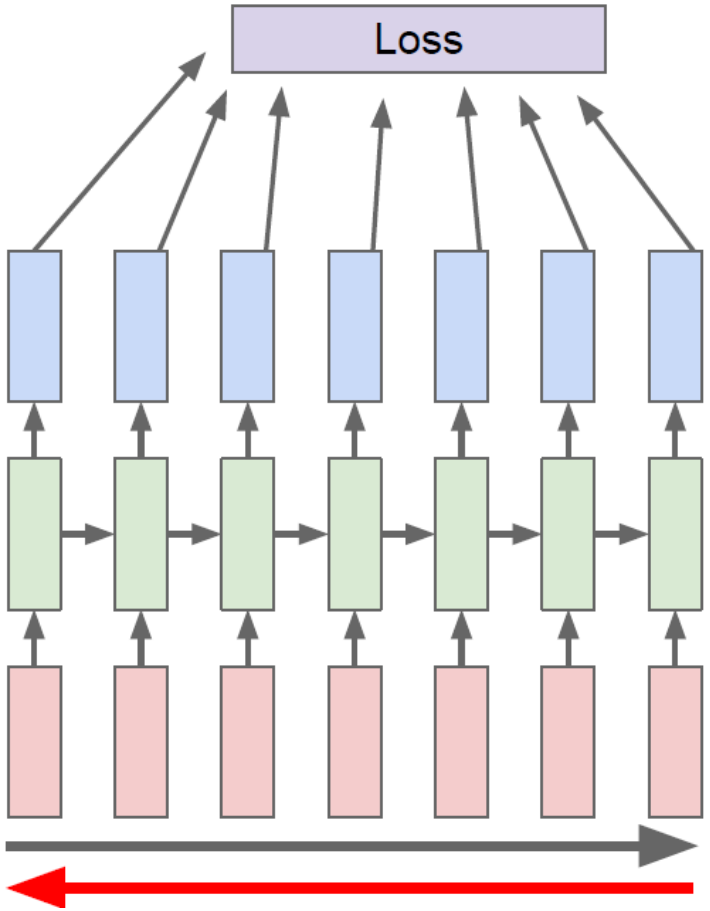
Test

Backpropagation по времени



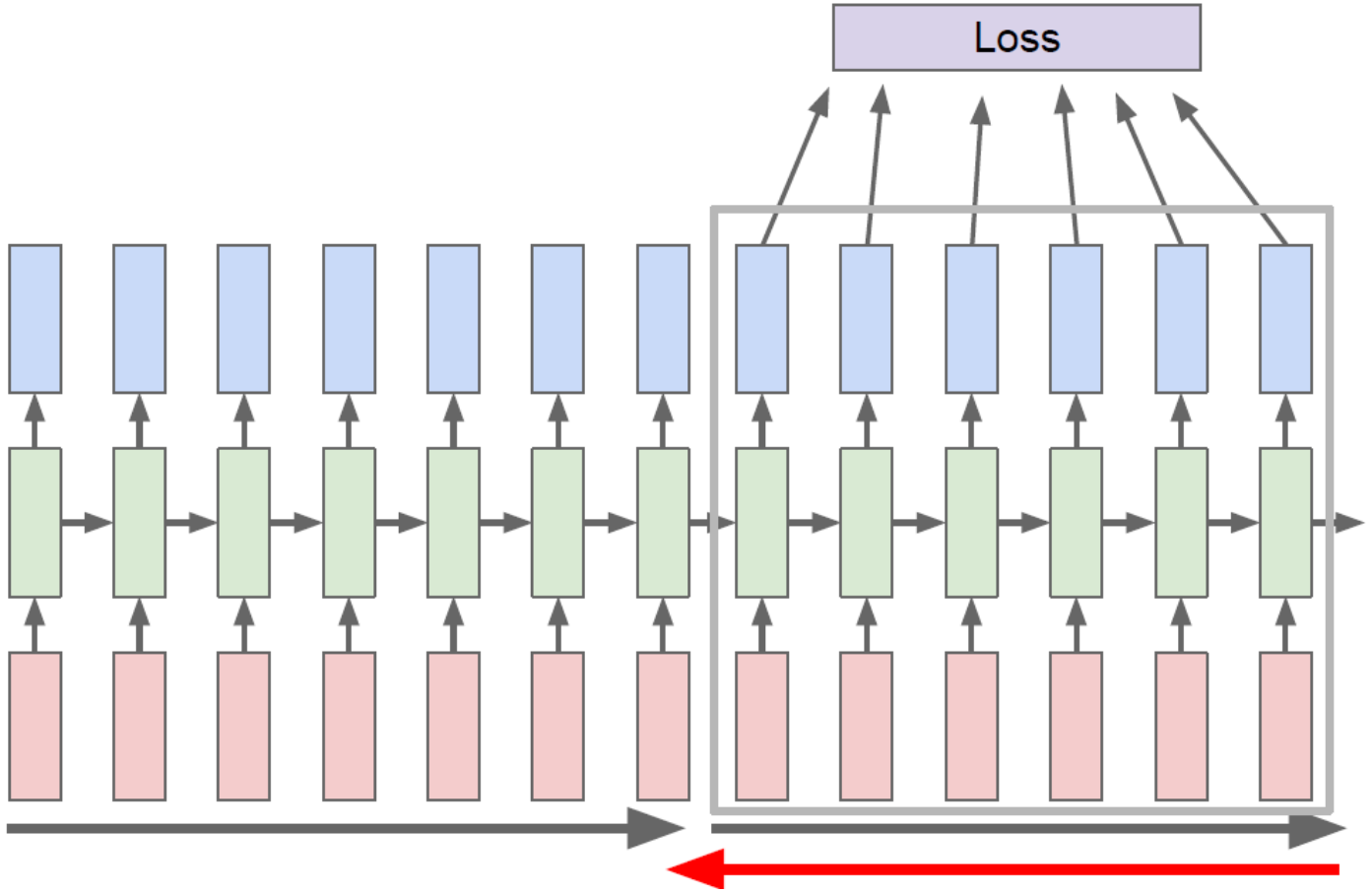
Прямой и обратный проход по всей последовательности

Truncated Backpropagation по времени



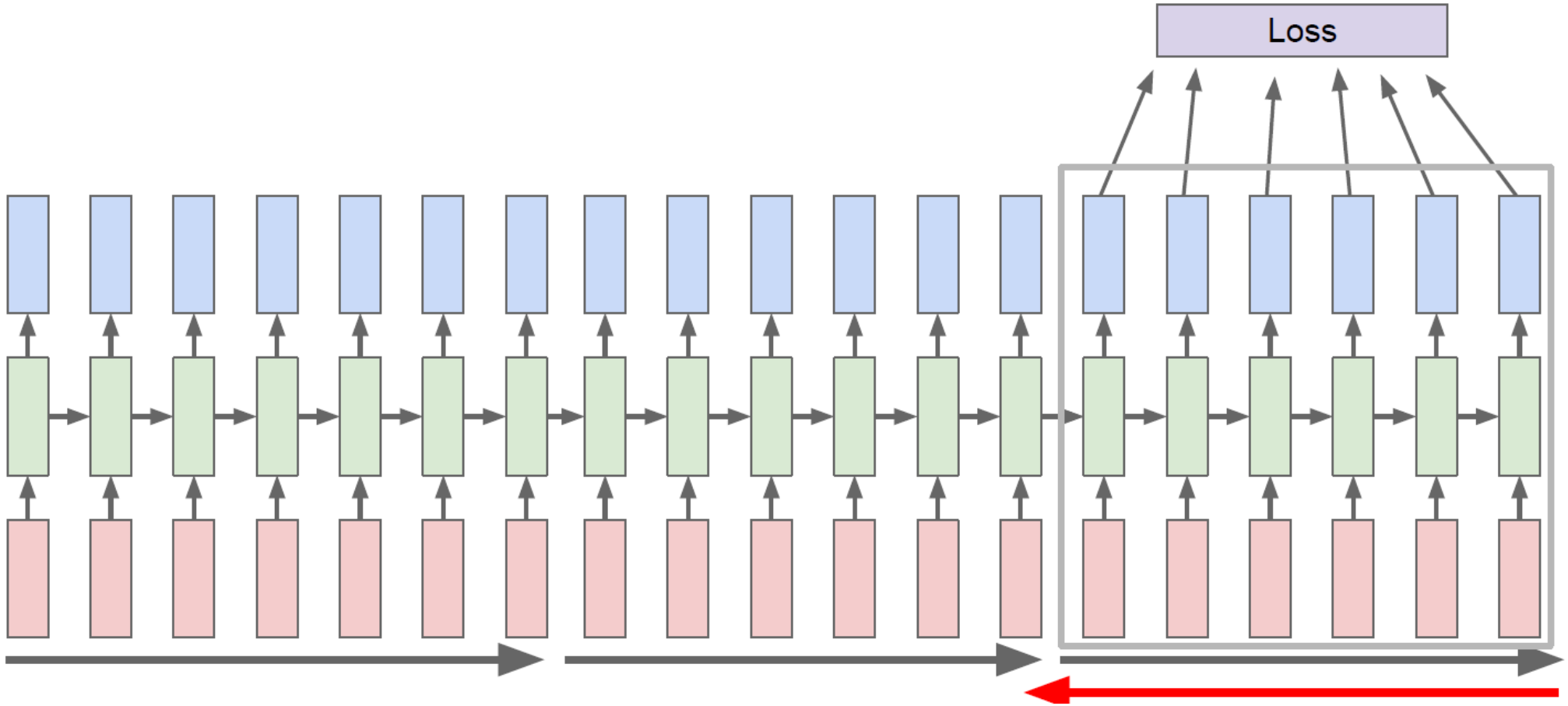
Прямой и обратный проход только по кусочку всей последовательности

Truncated Backpropagation по времени



Сохраняем состояния предыдущего кусочка и делаем прямой и обратный проход по следующему

Truncated Backpropagation по времени



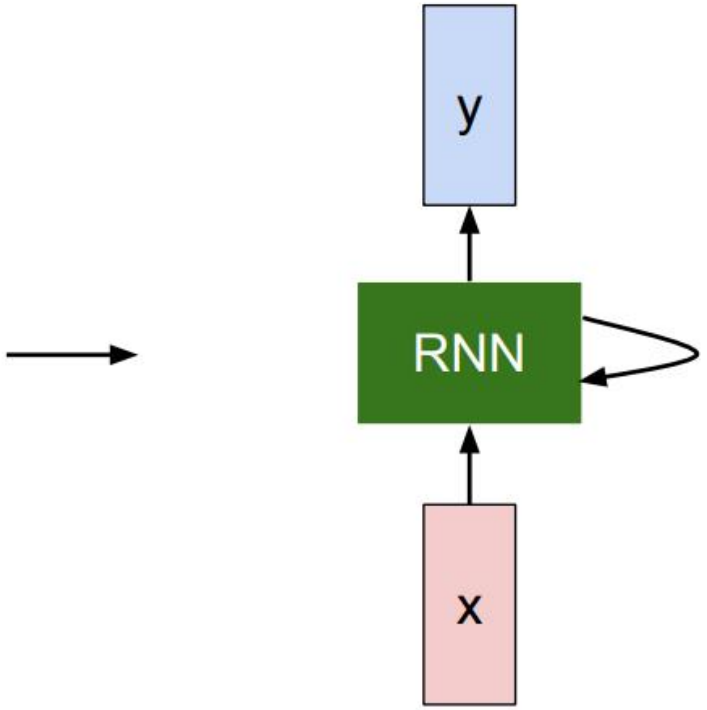
Примеры генерации текста

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.



Примеры генерации текста

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.
```

Визуализация скрытого состояния

Text color corresponds to tanh(c), where -1 is red and +1 is blue.

Cell sensitive to position in line:

```
The sole importance of the crossing of the Berezina lies in the fact
that it plainly and indubitably proved the fallacy of all the plans for
cutting off the enemy's retreat and the soundness of the only possible
line of action--the one Kutuzov and the general mass of the army
demanded--namely, simply to follow the enemy up. The French crowd fled
at a continually increasing speed and all its energy was directed to
reaching its goal. It fled like a wounded animal and it was impossible
to block its path. This was shown not so much by the arrangements it
made for crossing as by what took place at the bridges. When the bridges
broke down, unarmed soldiers, people from Moscow and women with children
who were with the French transport, all--carried on by vis inertiae--
pressed forward into boats and into the ice-covered water and did not,
surrender.
```

Cell that turns on inside quotes:

```
"You mean to imply that I have nothing to eat out of.... On the
contrary, I can supply you with everything even if you want to give
dinner parties," warmly replied Chichagov, who tried by every word he
spoke to prove his own rectitude and therefore imagined Kutuzov to be
animated by the same desire.

Kutuzov, shrugging his shoulders, replied with his subtle penetrating
smile: "I meant merely to say what I said."
```

Cell that robustly activates inside if statements:

```
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;
}
```

A large portion of cells are not easily interpretable. Here is a typical example:

```
/* Unpack a filter field's string representation from user-space
 * buffer. */
char *audit_unpack_string(void **bufp, size_t *remain, size_t len)
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /* Of the currently implemented string fields, PATH_MAX
   * defines the longest valid length.
   */
```

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;
}
```

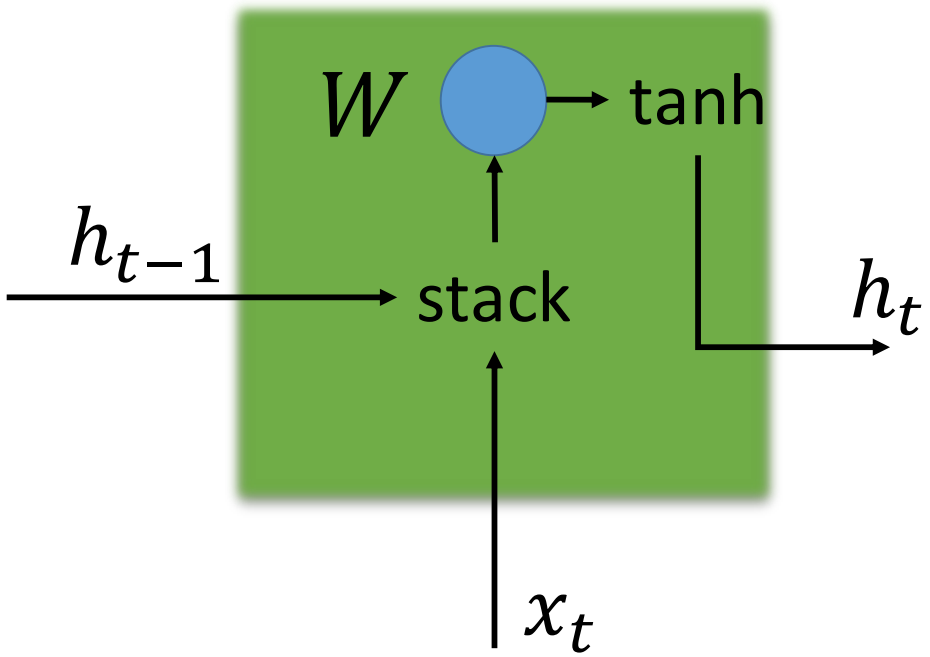
Cell that is sensitive to the depth of an expression:

```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
  int i;
  if (classes[class]) {
    for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
      if (mask[i] & classes[class][i])
        return 0;
  }
  return 1;
}
```

Cell that might be helpful in predicting a new line. Note that it only turns on for some ")":

```
char *audit_unpack_string(void **bufp, size_t *remain, si
{
  char *str;
  if (!*bufp || (len == 0) || (len > *remain))
    return ERR_PTR(-EINVAL);
  /* Of the currently implemented string fields, PATH_MAX
   * defines the longest valid length.
   */
  if (len > PATH_MAX)
    return ERR_PTR(-ENAMETOOLONG);
  str = kmalloc(len + 1, GFP_KERNEL);
  if (unlikely(!str))
    return ERR_PTR(-ENOMEM);
  memcpy(str, *bufp, len);
  str[len] = 0;
  *bufp += len;
  *remain -= len;
  return str;
}
```

Градиент через RNN



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

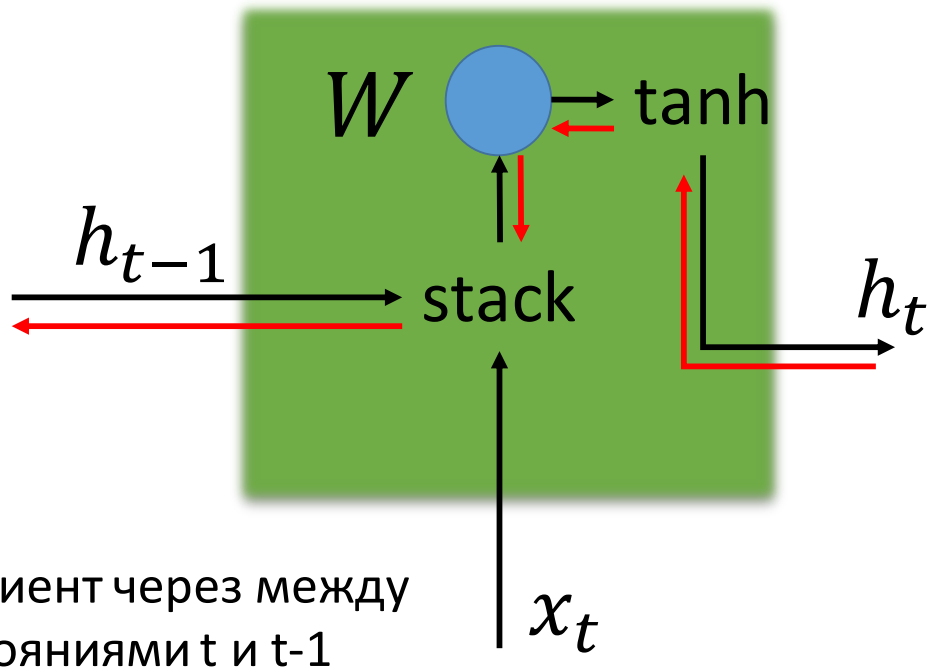
$$= \tanh((W_{hh} \quad W_{xh}) \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix})$$

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

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

Градиент через RNN



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

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

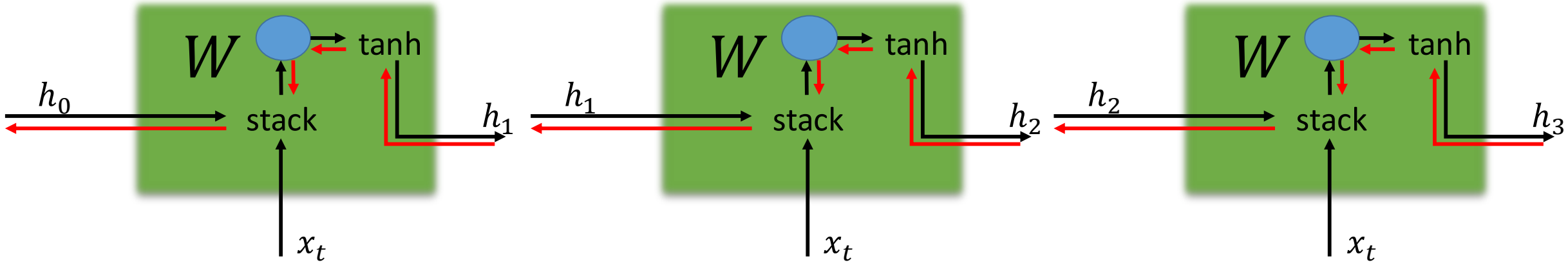
$$= \tanh(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix})$$

Градиент через между состояниями t и t-1 умножается на матрицу весов W^T

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

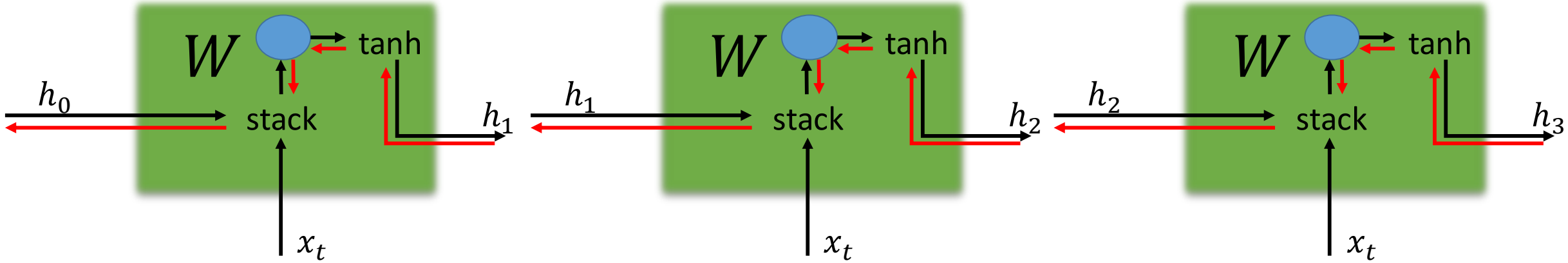
Pascanu et al, “On the difficulty of training recurrent neural networks”, ICML 2013

Градиент через RNN



Вычисление градиента для состояния 0 будет приводить к многократному умножению на матрицу весов *W*

Градиент через RNN

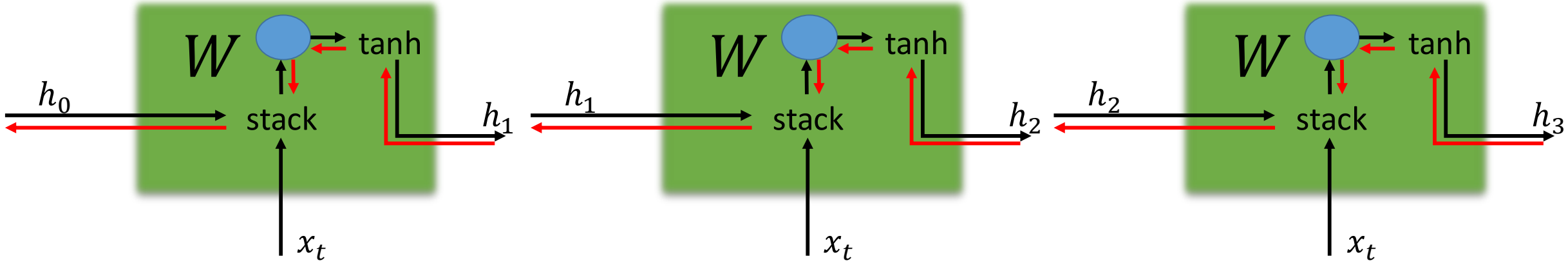


Вычисление градиента для состояния 0 будет приводить к многократному умножению на матрицу весов *W*

Значения матрицы больше 1:
Exploding gradient

Значения матрицы меньше 1:
Vanishing gradient

Градиент через RNN



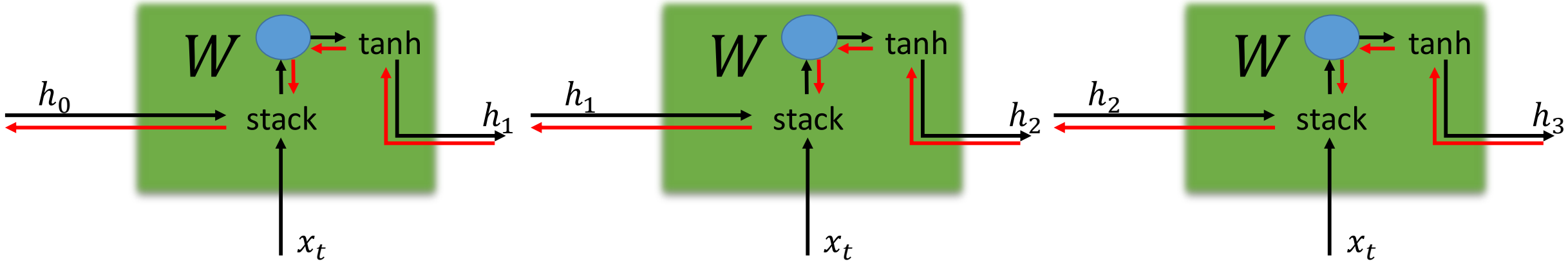
Вычисление градиента для состояния 0 будет приводить к многократному умножению на матрицу весов *W*

Значения матрицы больше 1:

Exploding gradient

```
torch.nn.utils.clip_grad_norm_( model.parameters(), 1)
```

Градиент через RNN



Вычисление градиента для состояния 0 будет приводить к многократному умножению на матрицу весов *W*

Значения матрицы меньше 1:

Vanishing gradient

Нужно менять архитектуру RNN

Проблемы RNN сетей

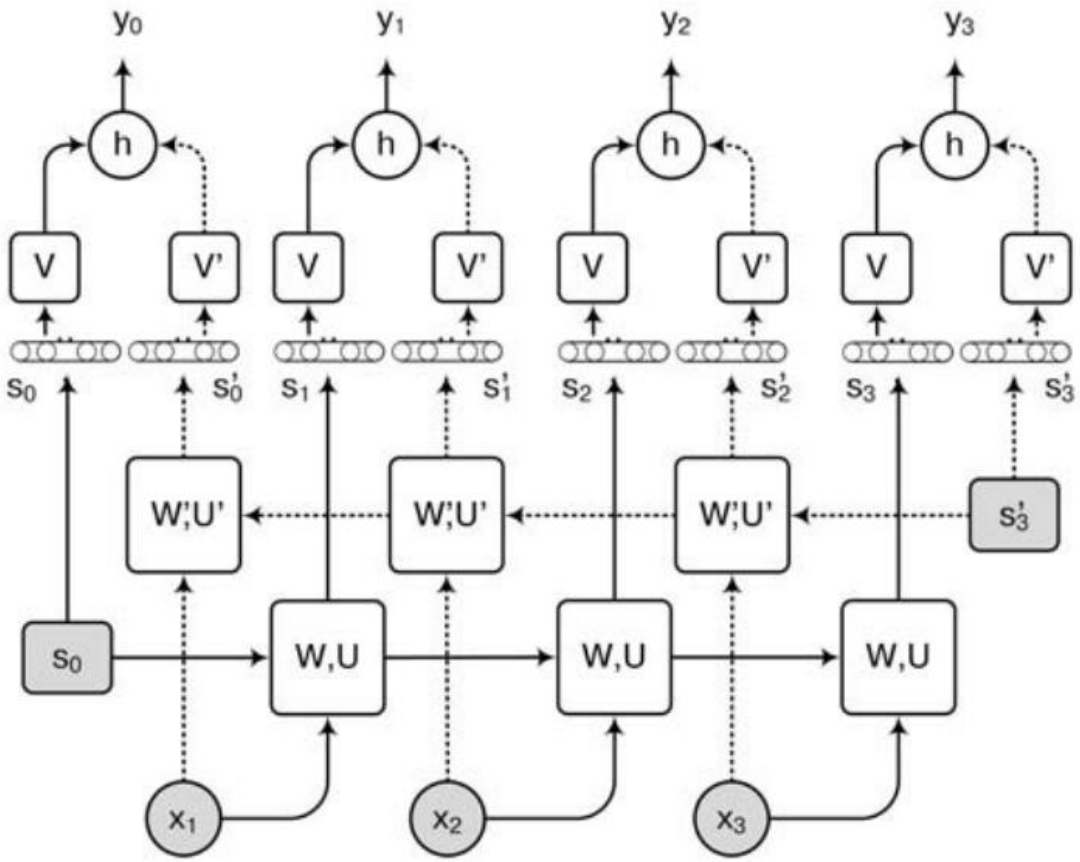
Не может видеть вперед

Решает при помощи bidirectional RNN.

Считаем два hidden_state

слева-направо и

справа-налево



$$\begin{aligned} \boldsymbol{s}_t &= \sigma\left(\boldsymbol{b} + W\boldsymbol{s}_{t-1} + U\boldsymbol{x}_t\right), & \boldsymbol{s}'_t &= \sigma\left(\boldsymbol{b}' + W'\boldsymbol{s}'_{t+1} + U'\boldsymbol{x}_t\right), \\ \boldsymbol{o}_t &= \boldsymbol{c} + V\boldsymbol{s}_t + V'\boldsymbol{s}'_t, & \boldsymbol{y}_t &= h\left(\boldsymbol{o}_t\right). \end{aligned}$$

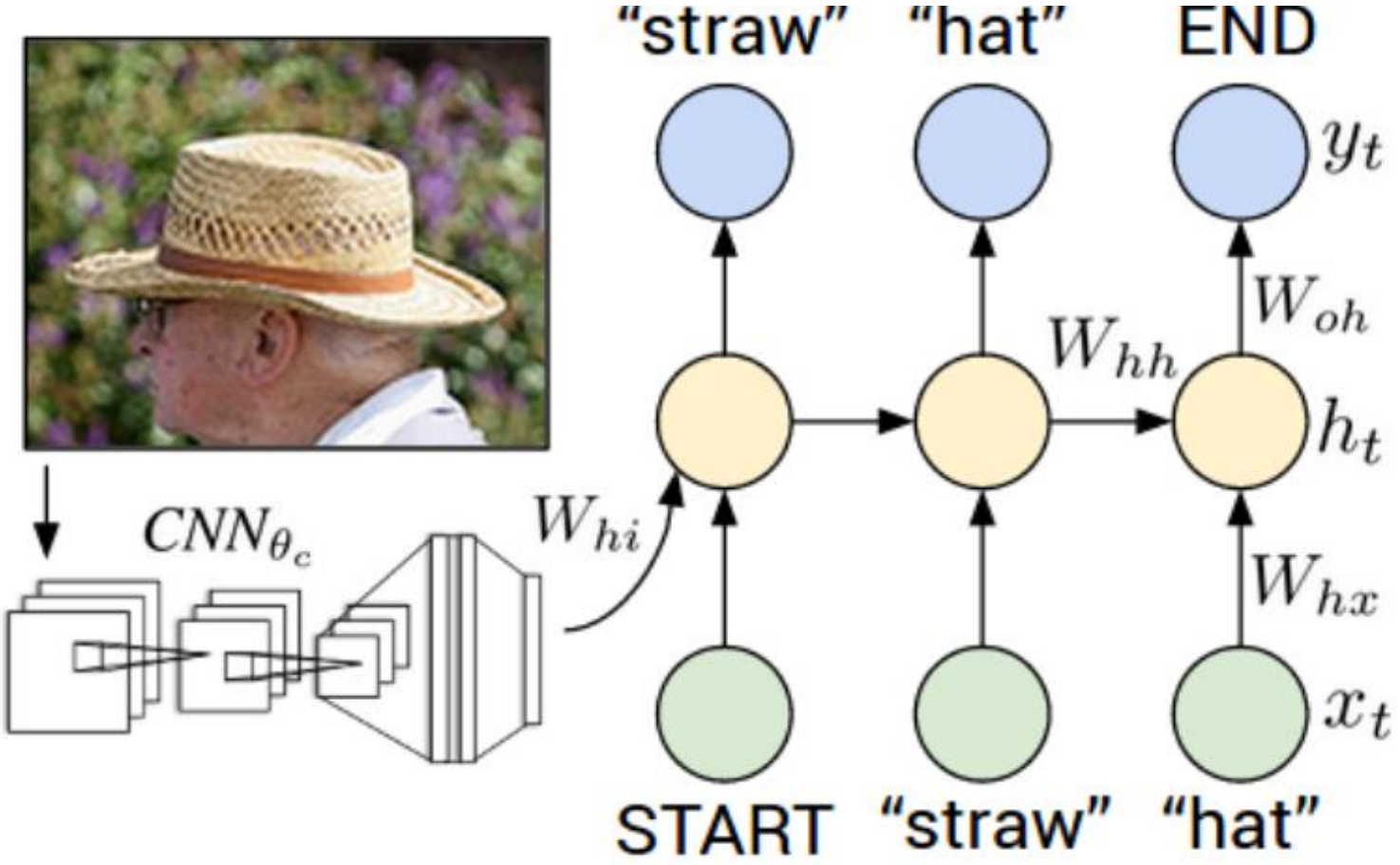
Проблемы RNN сетей

Не может видеть далеко назад - при прохождении градиента обратно – происходит экспоненциальное затухание градиента, чем дальше назад – тем больше затухает.

Решение - **LSTM**

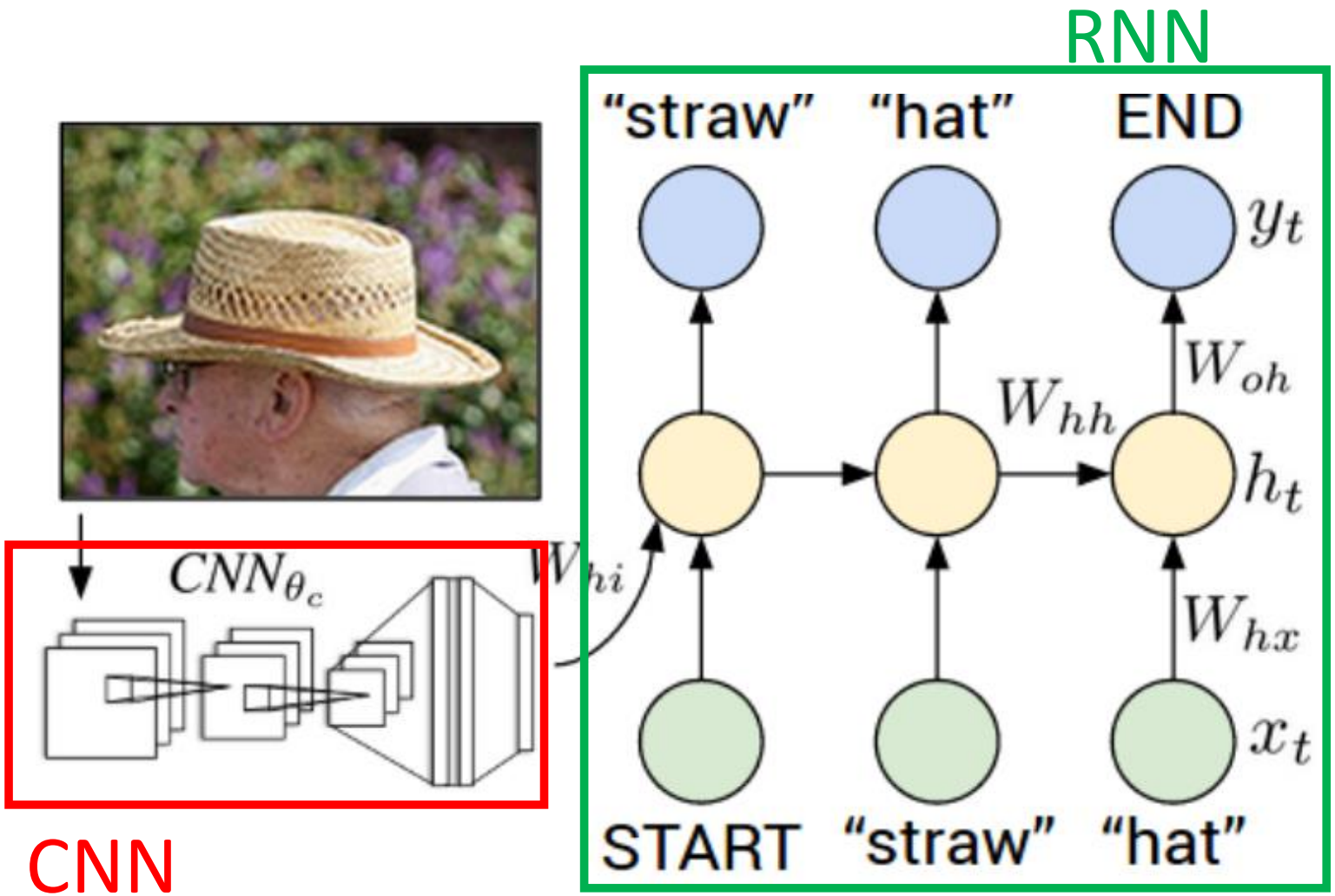
Приложения RNN сетей

Image Captioning



Deep Visual-Semantic Alignments for Generating Image Descriptions, Karpathy and Fei-Fei

Image Captioning



image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

FC-4096

FC-4096

FC-1000

softmax

X

test image

image

conv-64

conv-64

maxpool

conv-128

conv-128

maxpool

conv-256

conv-256

maxpool

conv-512

conv-512

maxpool

conv-512

conv-512

maxpool

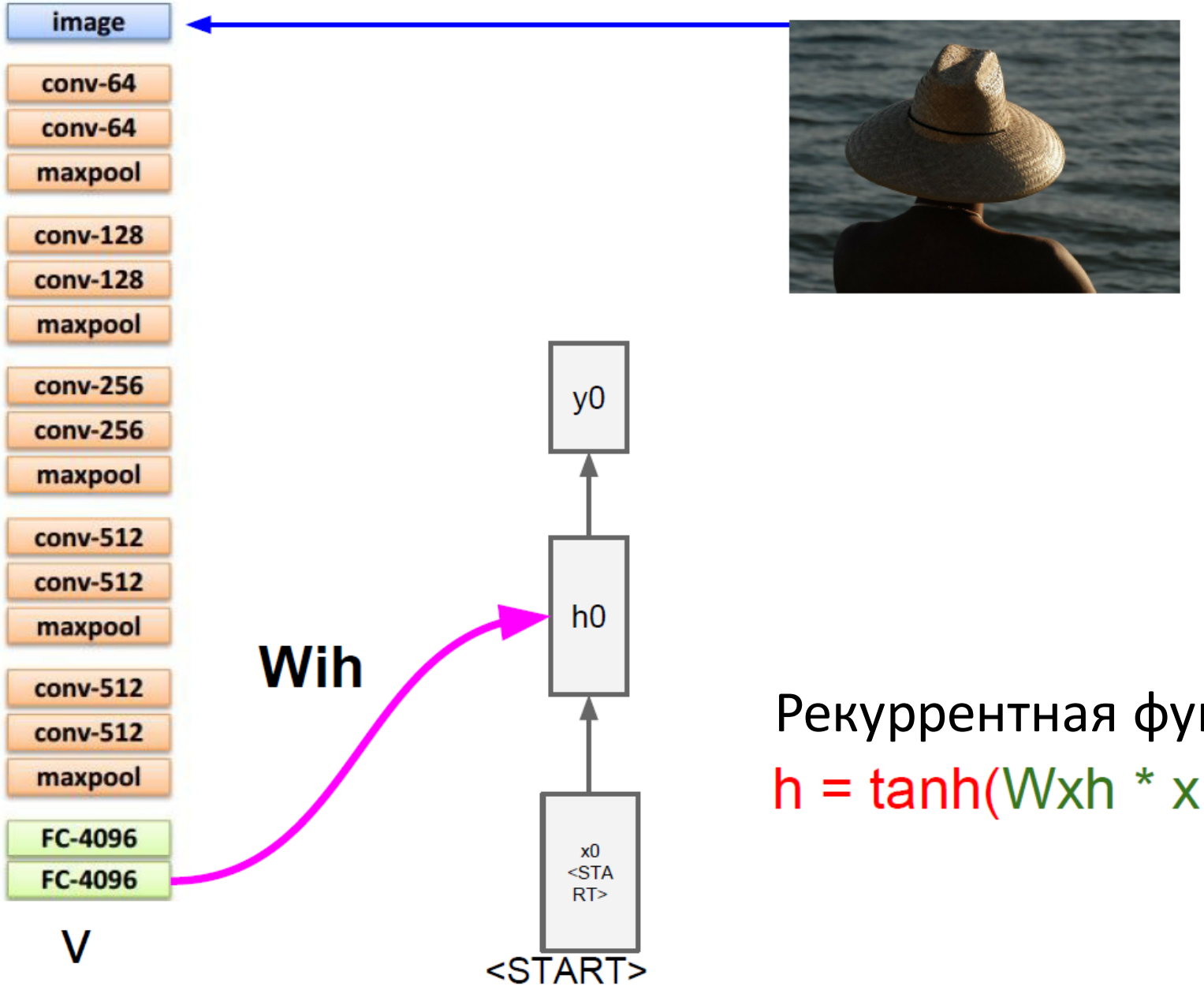
FC-4096

FC-4096

test image

x0
<STA
RT>

<START>



Рекуррентная функция

$$h = \tanh(W_{xh} * x + W_{hh} * h + W_{ih} * v)$$

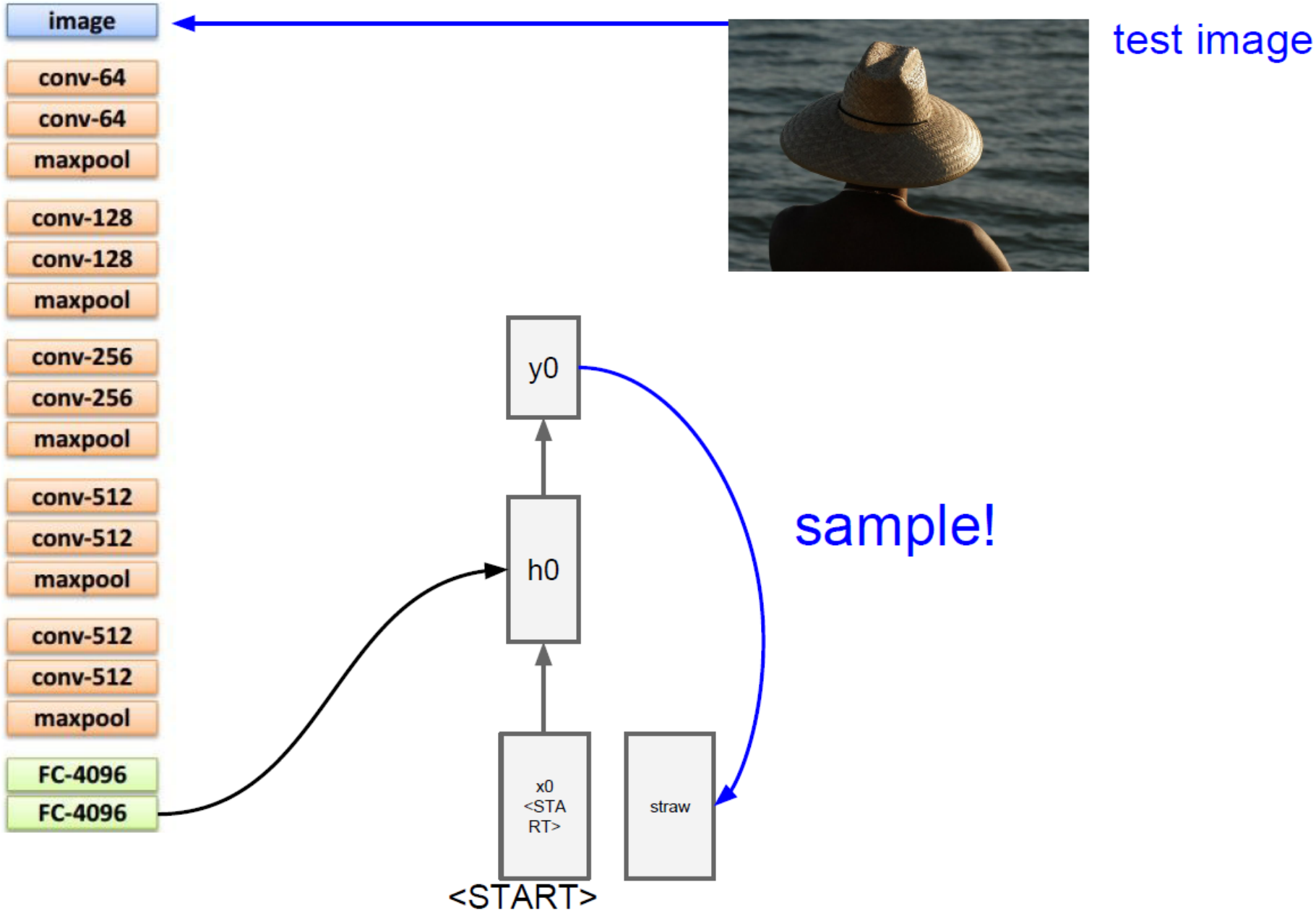
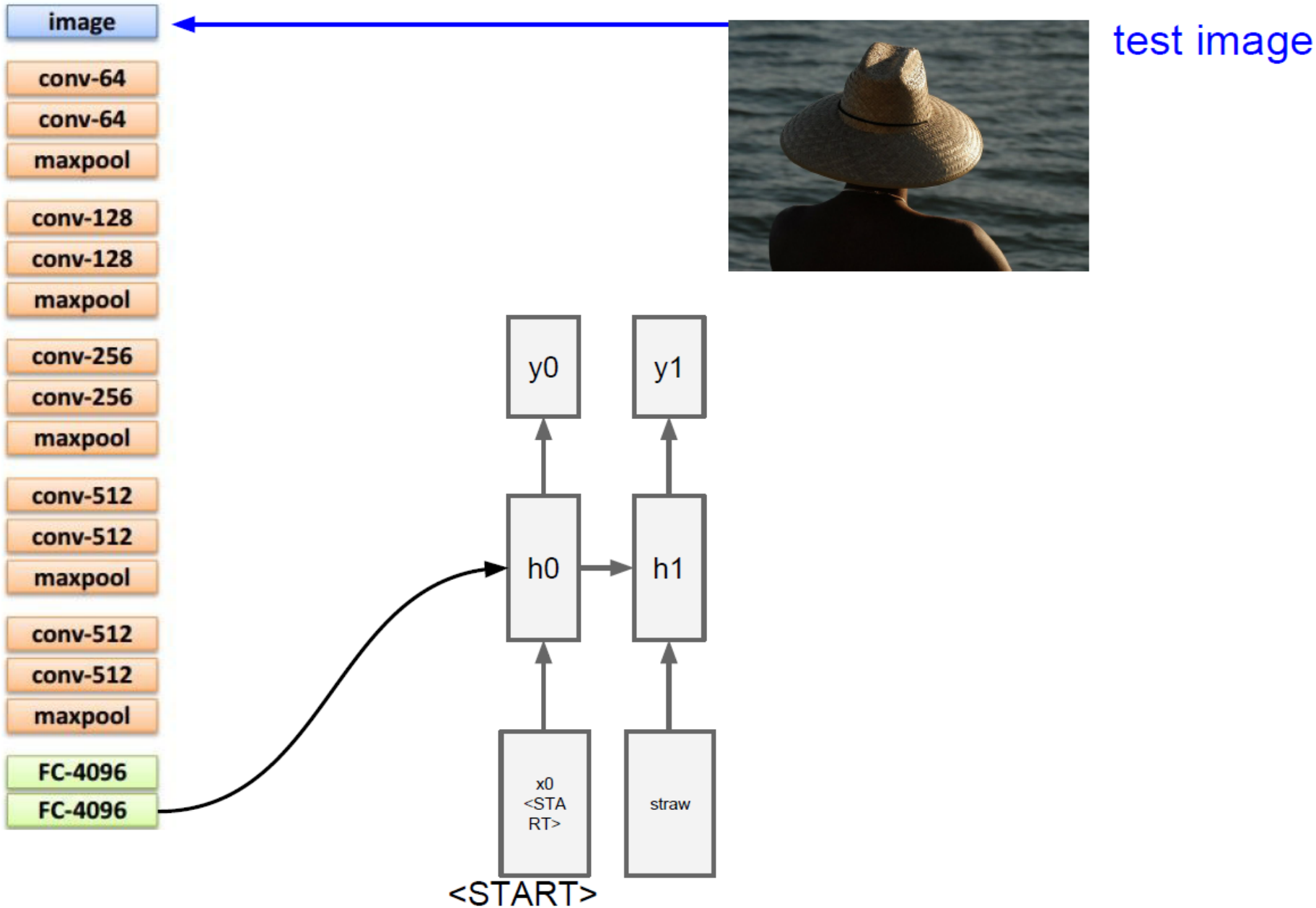


image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
h0
x0
<STA
RT>
straw
<START>
sample!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conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
h0
h1
x0
<STA
RT>
straw
<START>

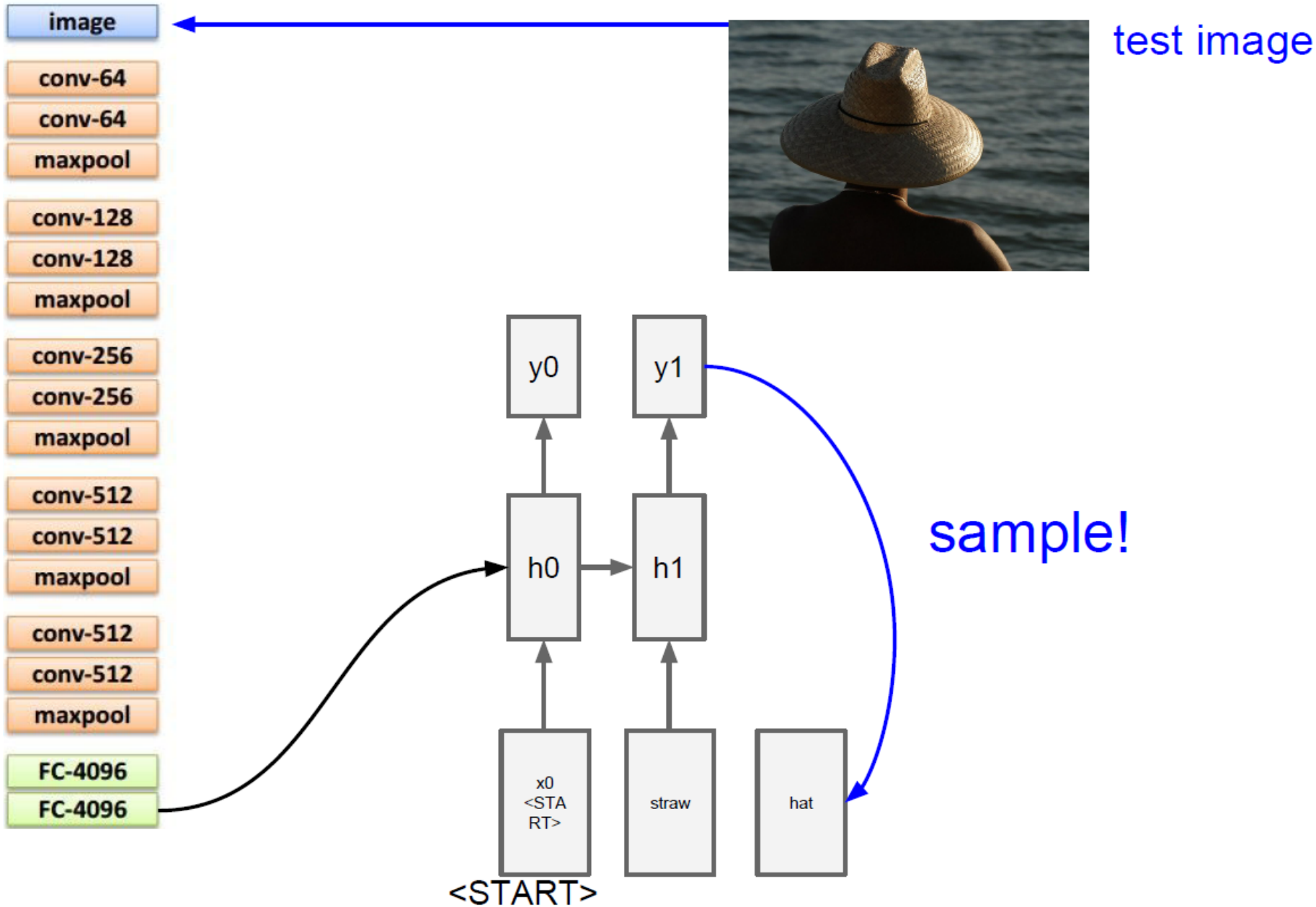


image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
h0
h1
x0
<STA
RT>
straw
hat
<START>
sample!

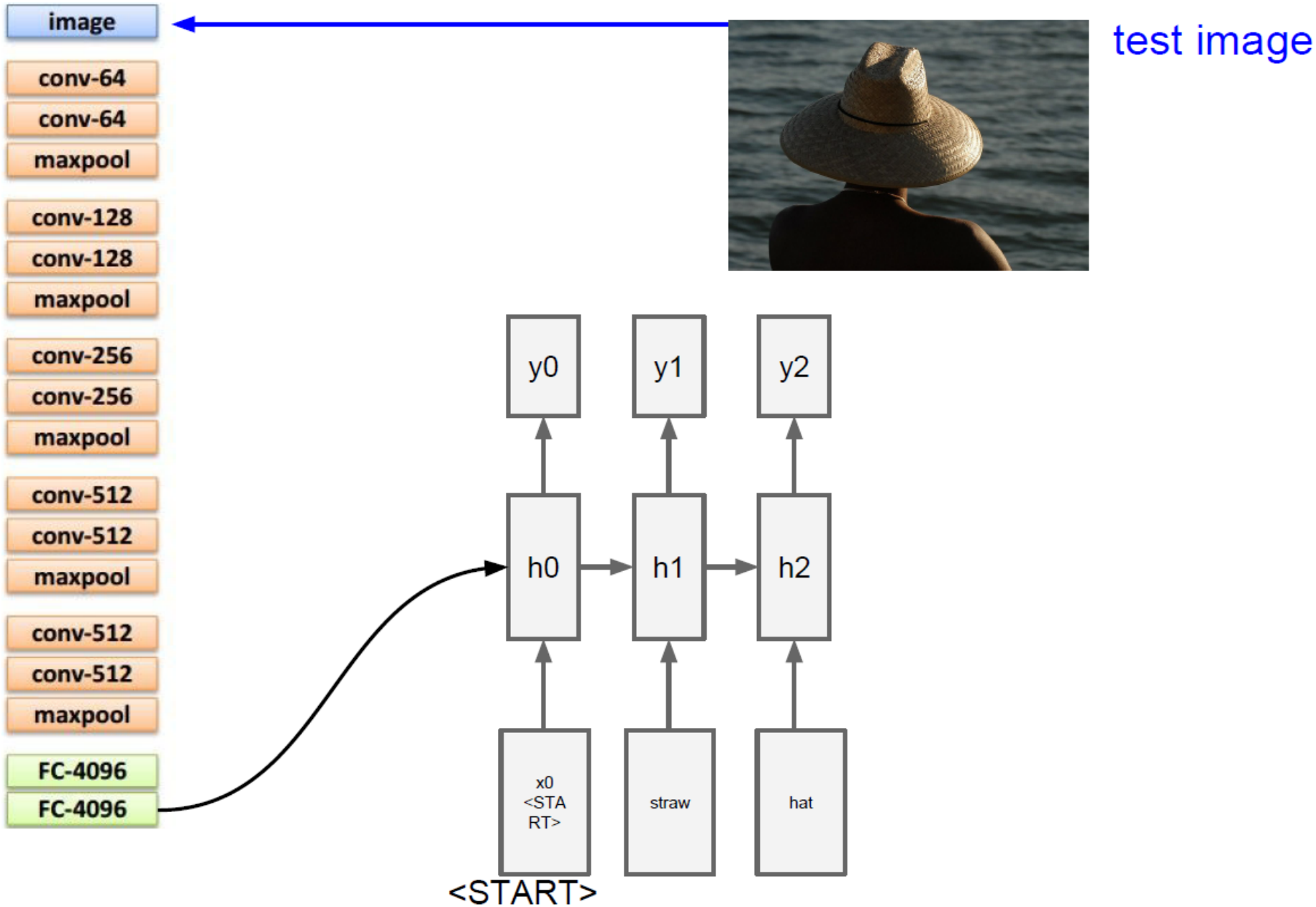


image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
y2
h0
h1
h2
x0
<STA
RT>
straw
hat
<START>

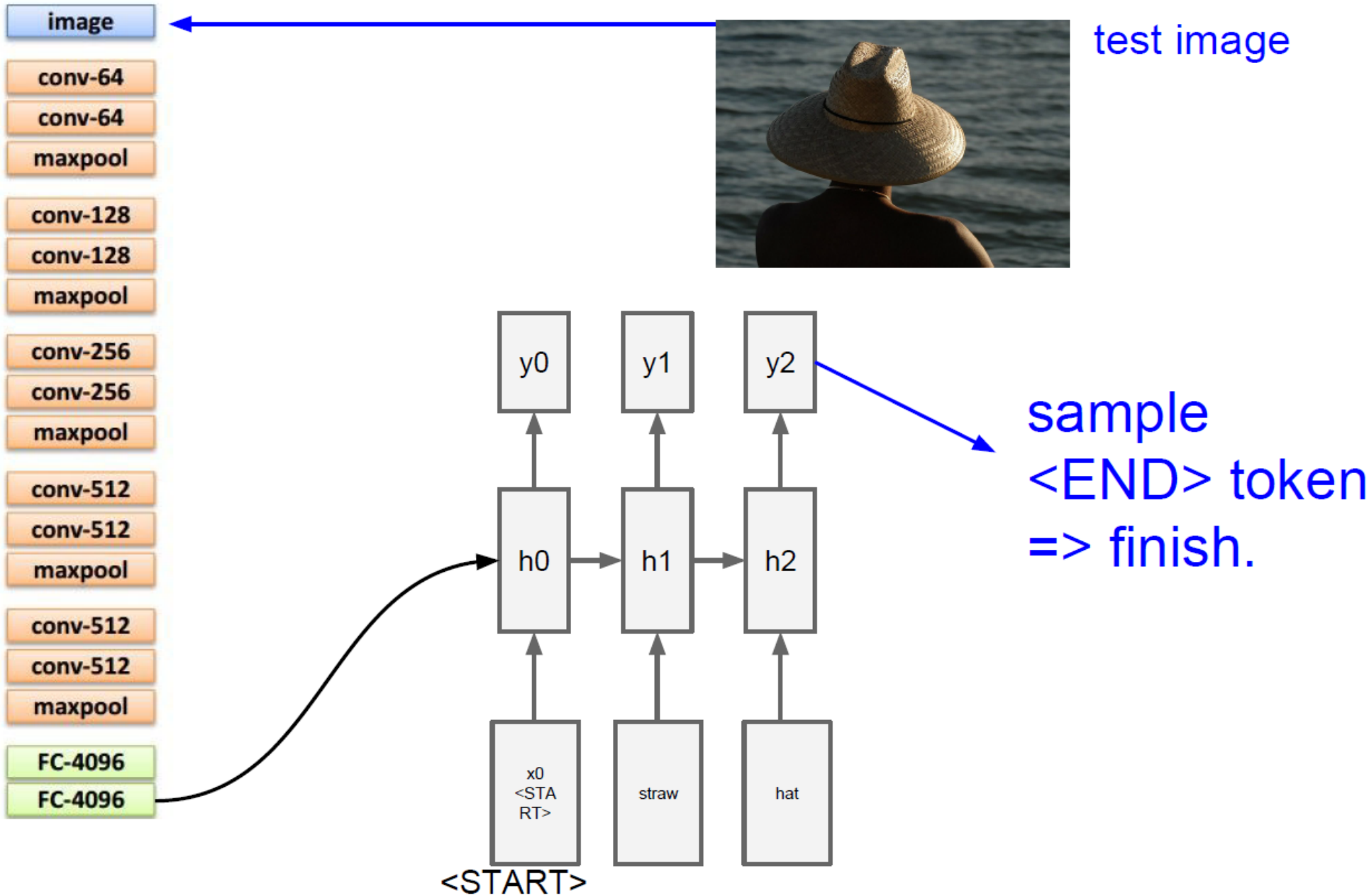
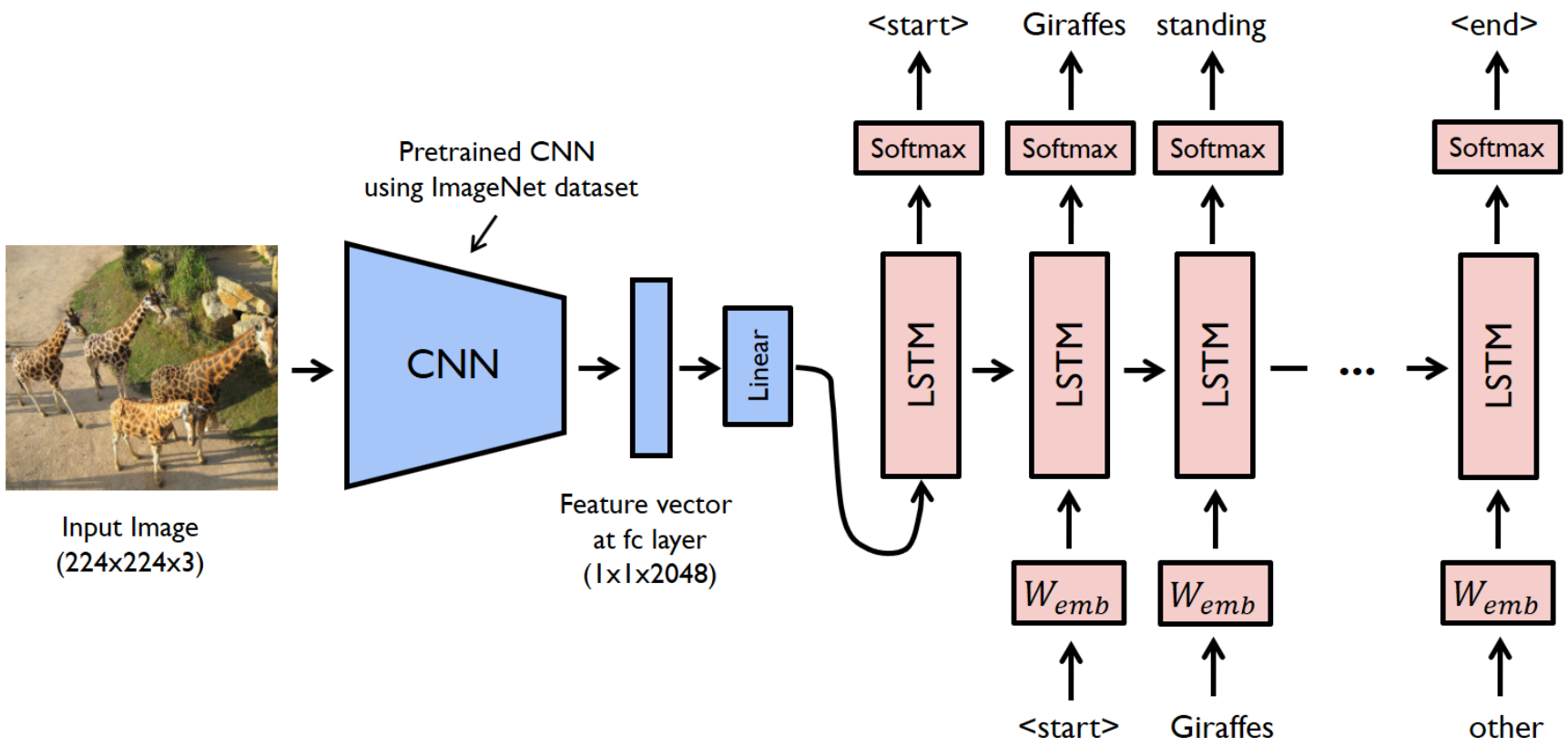


image
conv-64
conv-64
maxpool
conv-128
conv-128
maxpool
conv-256
conv-256
maxpool
conv-512
conv-512
maxpool
conv-512
conv-512
maxpool
FC-4096
FC-4096
test image
y0
y1
y2
h0
h1
h2
x0
<STA
RT>
straw
hat
<START>
sample
<END> token
=> finish.

Практика. Image Captioning



Пример работы. Image Captioning

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

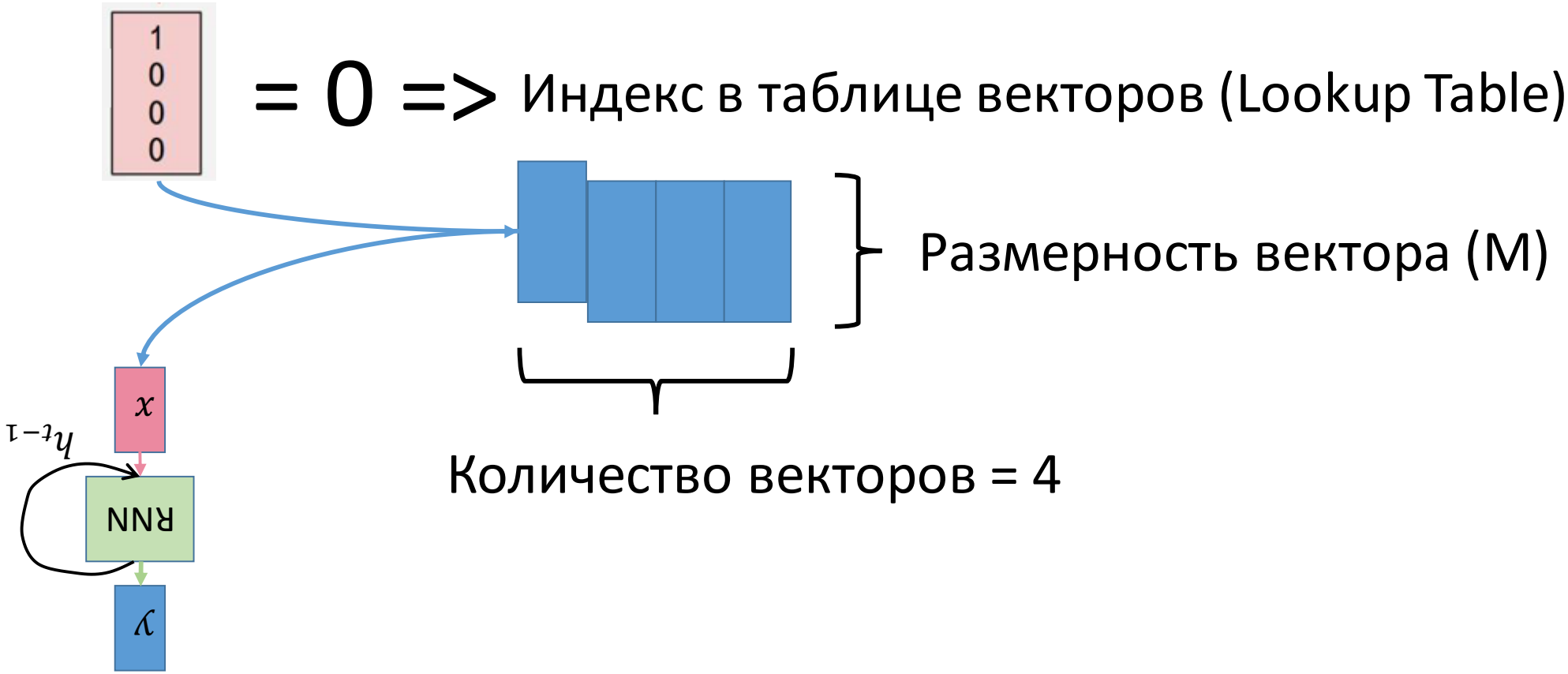
A tennis player in action on the court

Two giraffes standing in a grassy field

A man riding a dirt bike on a dirt track

Практика. Embedding.

- Входной вектор удобно представлять не как one-hot-encoding



Практика построения батчей текстов

1. Разбить текст на окна равной длинны
   - Минусы - внезапно начинается и оканчивается текст
2. Поделить текст по предложениям, добавить вначале и конце спец. Символы START, END и сделать все их одинакового размера используя FILLER
3. Вариант аналогичный первому - но надо всегда передавать скрытые состояния вначале окна. Сильно сложнее реализуется в framework-ax

Практика. Embedding.

class **torch.nn.Embedding**(*num_embeddings, embedding_dim, padding_idx=None, max_norm=None, norm_type=2, scale_grad_by_freq=False, sparse=False*) [source]

A simple lookup table that stores embeddings of a fixed dictionary and size.

This module is often used to store word embeddings and retrieve them using indices. The input to the module is a list of indices, and the output is the corresponding word embeddings.

Parameters:

- **num_embeddings** (*int*) – size of the dictionary of embeddings
- **embedding_dim** (*int*) – the size of each embedding vector
- **padding_idx** (*int, optional*) – If given, pads the output with zeros whenever it encounters the index.
- **max_norm** (*float, optional*) – If given, will renormalize the embeddings to always have a norm lesser than this
- **norm_type** (*float, optional*) – The p of the p-norm to compute for the max_norm option
- **scale_grad_by_freq** (*boolean, optional*) – if given, this will scale gradients by the frequency of the words in the mini-batch.
- **sparse** (*boolean, optional*) – if `True`, gradient w.r.t. weight matrix will be a sparse tensor. See Notes for more details regarding sparse gradients.

Variables: **weight** (*Tensor*) – the learnable weights of the module of shape (num_embeddings, embedding_dim)

Shape:

- Input: LongTensor *(N, W)*, N = mini-batch, W = number of indices to extract per mini-batch

class `torch.nn.LSTM`(**args*, ***kwargs*) [source]

Applies a multi-layer long short-term memory (LSTM) RNN to an input seque

For each element in the input sequence, each layer computes the following fu

$$
\begin{aligned}
i_t &= \text{sigmoid}(W_{ii}x_t + b_{ii} + W_{hi}h_{(t-1)} + b_{hi}) \\
f_t &= \text{sigmoid}(W_{if}x_t + b_{if} + W_{hf}h_{(t-1)} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hc}h_{(t-1)} + b_{hg}) \\
o_t &= \text{sigmoid}(W_{io}x_t + b_{io} + W_{ho}h_{(t-1)} + b_{ho}) \\
c_t &= f_t * c_{(t-1)} + i_t * g_t \\
h_t &= o_t * \tanh(c_t)
\end{aligned}
$$

where h_t is the hidden state at time *t*, c_t is the cell state at time *t*, x_t is the hid previous layer at time *t* or $input_t$ for the first layer, and i_t, f_t, g_t, o_t are the in out gates, respectively.

Parameters:

- **input_size** – The number of expected features in the input x
- **hidden_size** – The number of features in the hidden state h
- **num_layers** – Number of recurrent layers.
- **bias** – If `False`, then the layer does not use bias weights b_ih and b_hh. Default: `True`
- **batch_first** – If `True`, then the input and output tensors are provided as (batch, seq, feature)
- **dropout** – If non-zero, introduces a dropout layer on the outputs of each RNN layer except the last layer
- **bidirectional** – If `True`, becomes a bidirectional RNN. Default: `False`

Inputs: input, (h_0, c_0)

- **input** (seq_len, batch, input_size): tensor containing the features of the input sequence. The input can also be a packed variable length sequence. See `torch.nn.utils.rnn.pack_padded_sequence()` for details.
- **h_0** (num_layers * num_directions, batch, hidden_size): tensor containing the initial hidden state for each element in the batch.
- **c_0** (num_layers * num_directions, batch, hidden_size): tensor containing the initial cell state for each element in the batch.

Outputs: output, (h_n, c_n)

- **output** (seq_len, batch, hidden_size * num_directions): tensor containing the output features *(h_t)* from the last layer of the RNN, for each t. If a `torch.nn.utils.rnn.PackedSequence` has been given as the input, the output will also be a packed sequence.
- **h_n** (num_layers * num_directions, batch, hidden_size): tensor containing the hidden state for t=seq_len
- **c_n** (num_layers * num_directions, batch, hidden_size): tensor containing the cell state for t=seq_len

Примеры RNN сетей

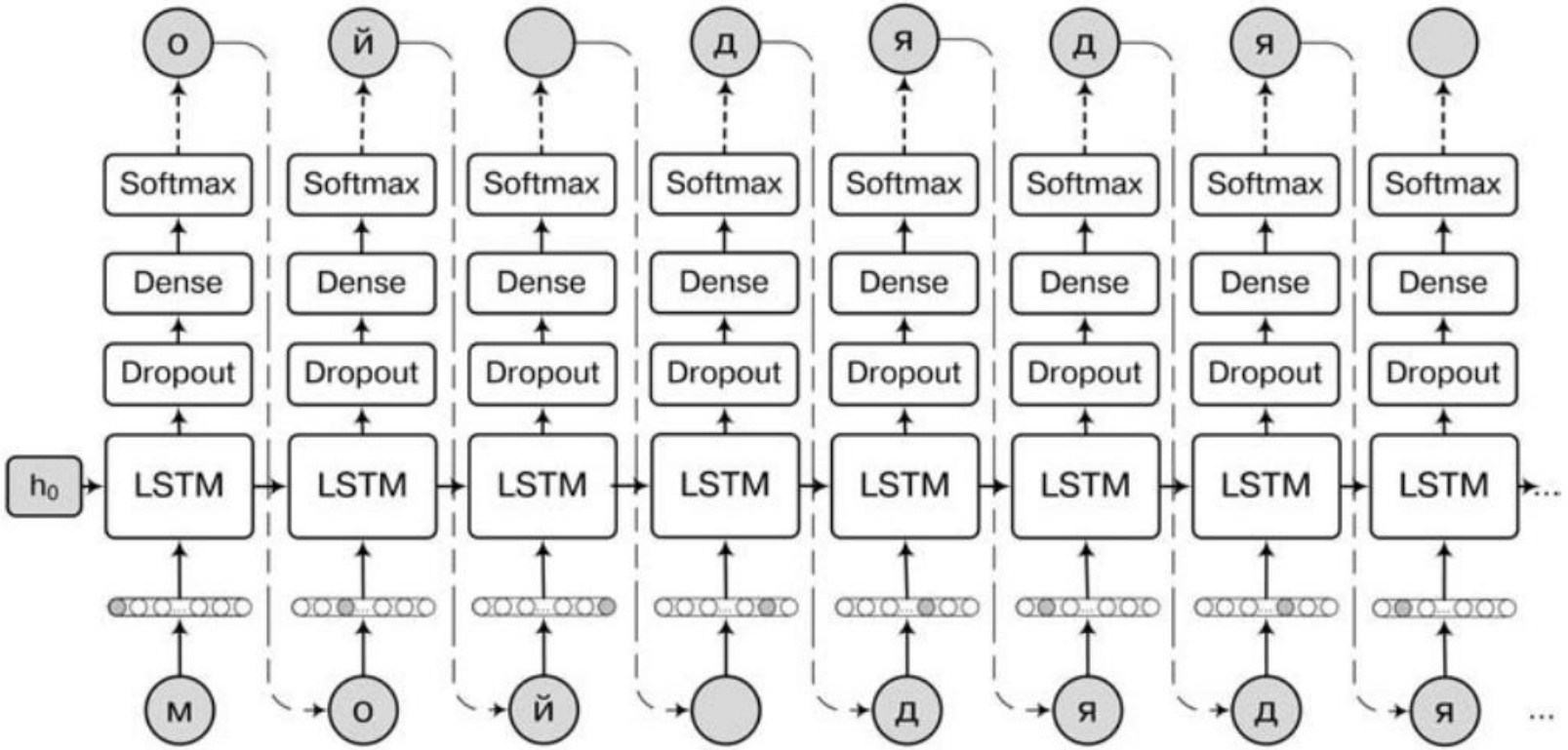


Рис. 6.12. Архитектура нейронной сети для посимвольного порождения текстов на основе одного уровня LSTM-ячеек

Примеры RNN сетей

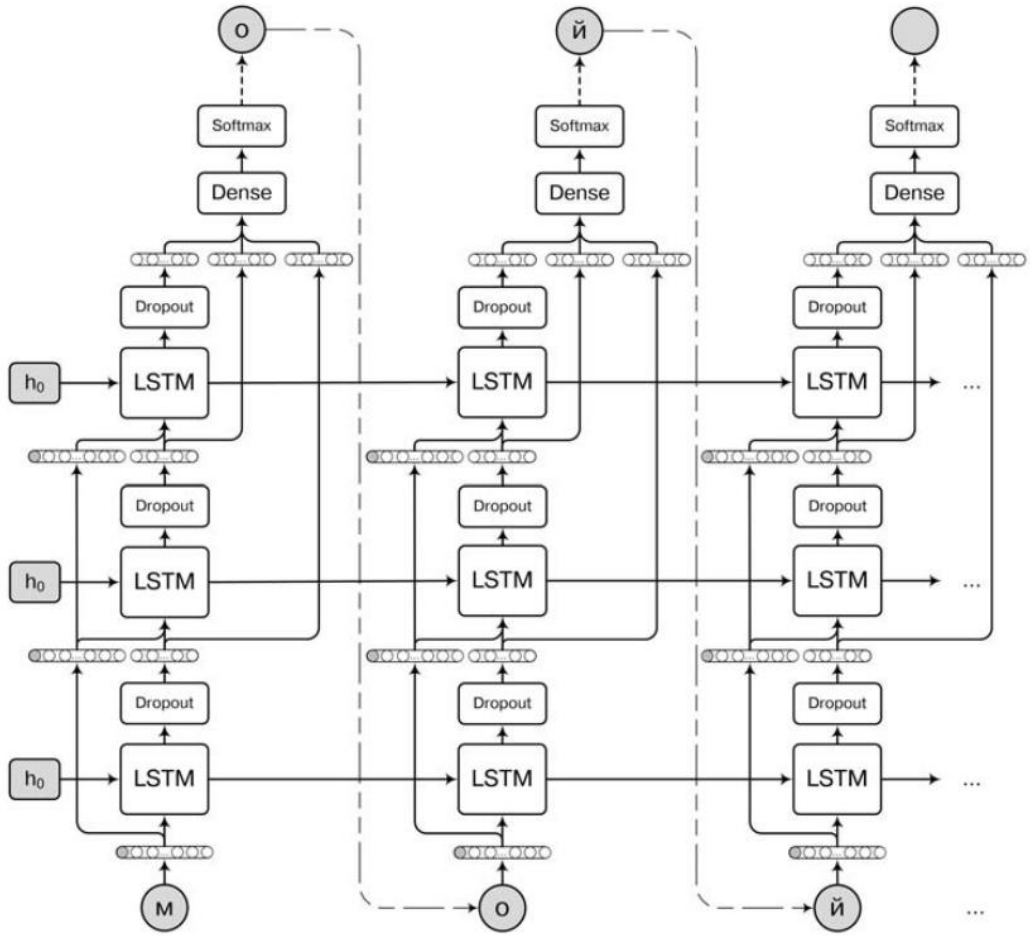


Рис. 6.13. Архитектура нейронной сети для посимвольного порождения текстов на основе трех уровней LSTM-ячеек

Примеры RNN сетей

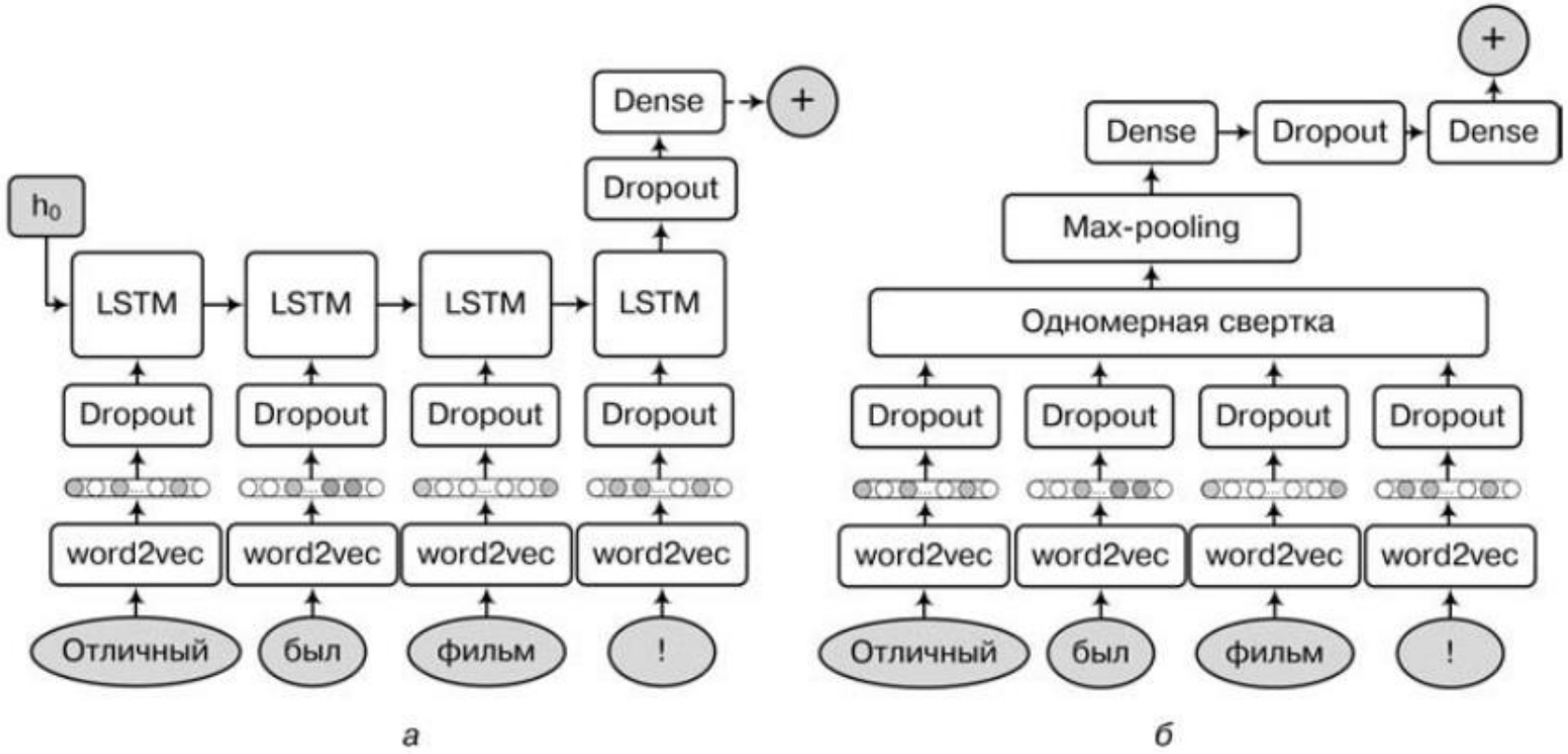


Рис. 7.5. Примеры нейронных сетей для задачи анализа тональности [64]:
а — рекуррентная; *б* — сверточная

Attention - следующая лекция подробнее

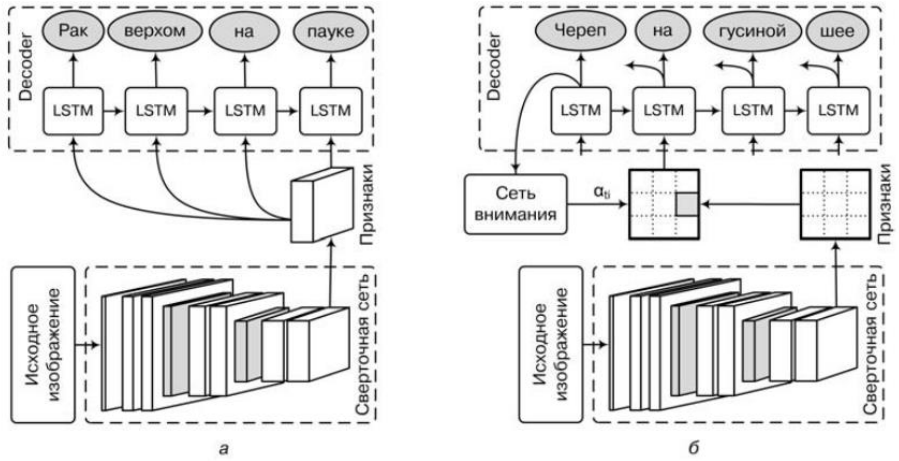


Рис. 8.2. Модели для порождения подписей к картинкам:
а — Show and Tell; *б* — Show, Attend and Tell

- *жесткое* (hard attention), в котором веса α_{ti} интерпретируются как вероятности событий s_{ti} того, что модель «посмотрит» в момент времени t на часть изображения i, и на вход рекуррентной сети для порождения текста подается представление той части изображения $\boldsymbol{a}_{i^*}$, которая выпадет на кубике с вероятностями α_{ti};
- *мягкое* (soft attention), когда на вход рекуррентной сети подается, можно сказать, ожидание вектора из s_{ti}, $\sum_k \alpha_{ti}\boldsymbol{a}_i$, то есть модель в каждый момент «смотрит» на все части изображения, просто некоторые из них играют более важную роль, чем другие.

Перерыв и потом LSTM

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

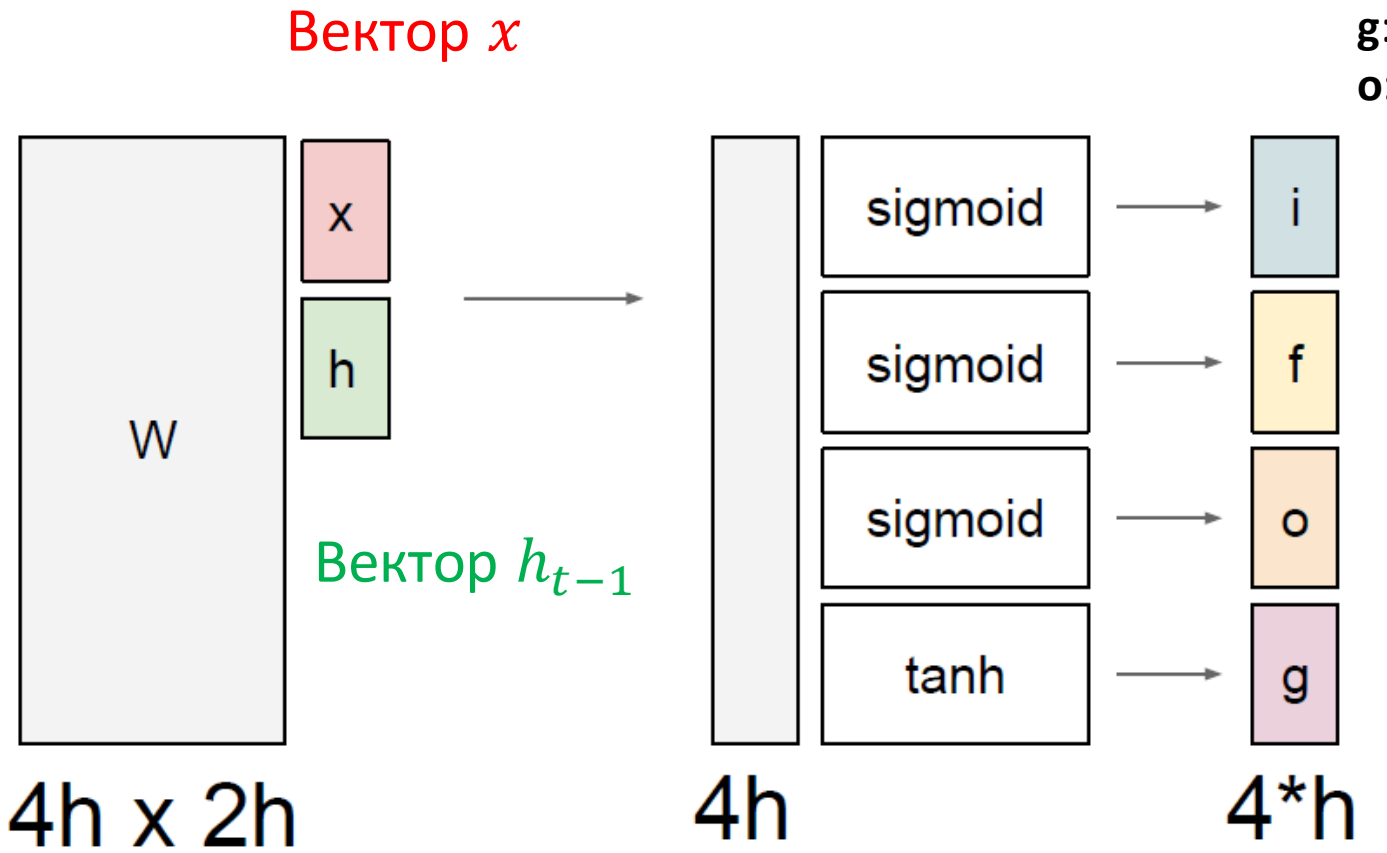
Long Short Term Memory (LSTM)

$$
\begin{aligned}
\boldsymbol{c}'_t &= \tanh\left(W_{xc}\boldsymbol{x}_t + W_{hc}\boldsymbol{h}_{t-1} + \boldsymbol{b}_{c'}\right) && \textit{candidate cell state} \\
\boldsymbol{i}_t &= \sigma\left(W_{xi}\boldsymbol{x}_t + W_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i\right) && \textit{input gate} \\
\boldsymbol{f}_t &= \sigma\left(W_{xf}\boldsymbol{x}_t + W_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{b}_f\right) && \textit{forget gate} \\
\boldsymbol{o}_t &= \sigma\left(W_{xo}\boldsymbol{x}_t + W_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o\right) && \textit{output gate} \\
\boldsymbol{c}_t &= \boldsymbol{f}_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{c}'_t, && \textit{cell state} \\
\boldsymbol{h}_t &= \boldsymbol{o}_t \odot \tanh(\boldsymbol{c}_t) && \textit{block output}
\end{aligned}
$$

$$y_t = W_{hy}\, h_t$$

Long Short Term Memory (LSTM)

f: Forget gate, Забывать ли состояние элемента
i: Input gate, Писать ли состояние элемента
g: Gate gate, Сколько писать в элемент
o: Output gate, Сколько выводить из элемента

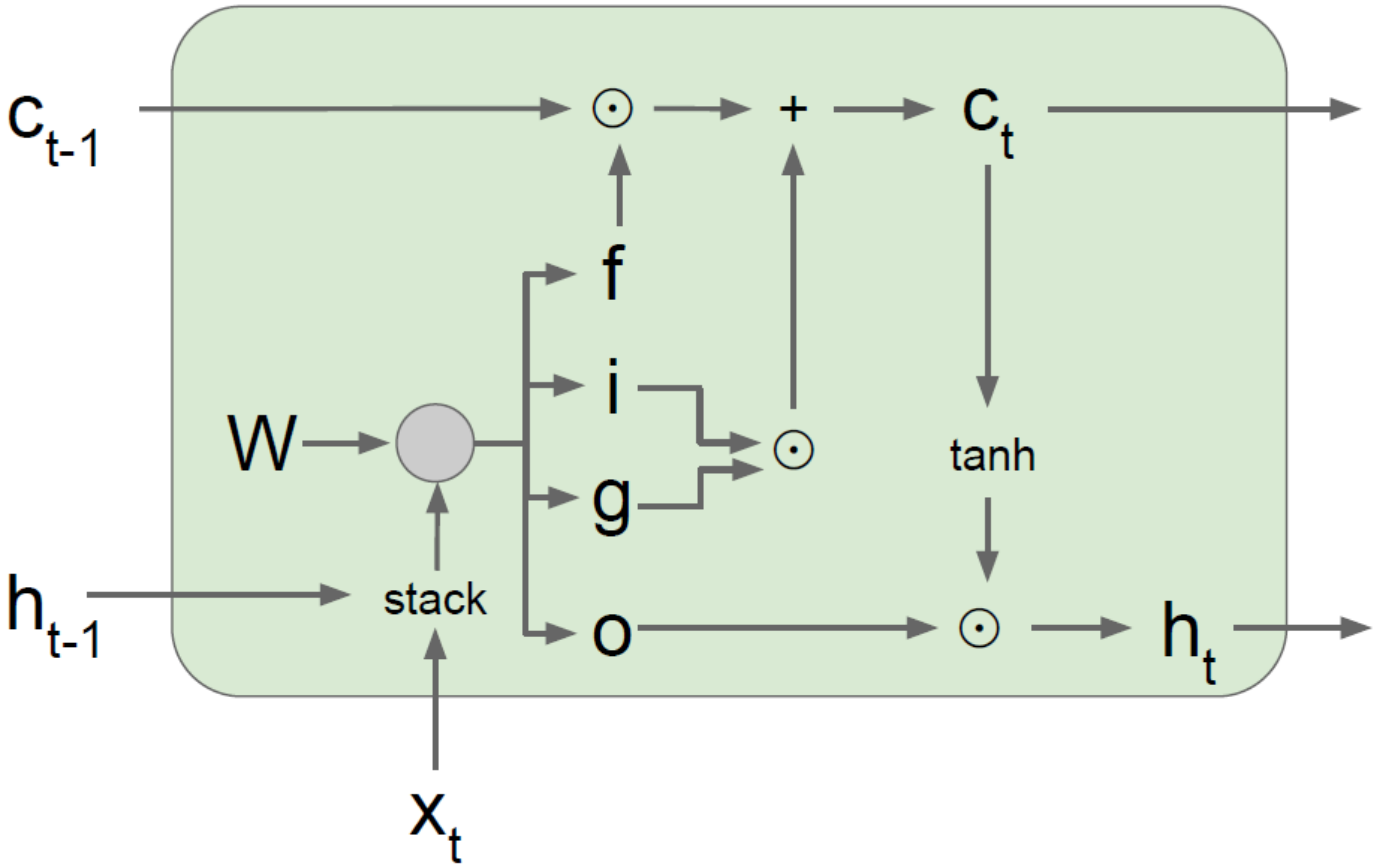


$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

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

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

Long Short Term Memory (LSTM)



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

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

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

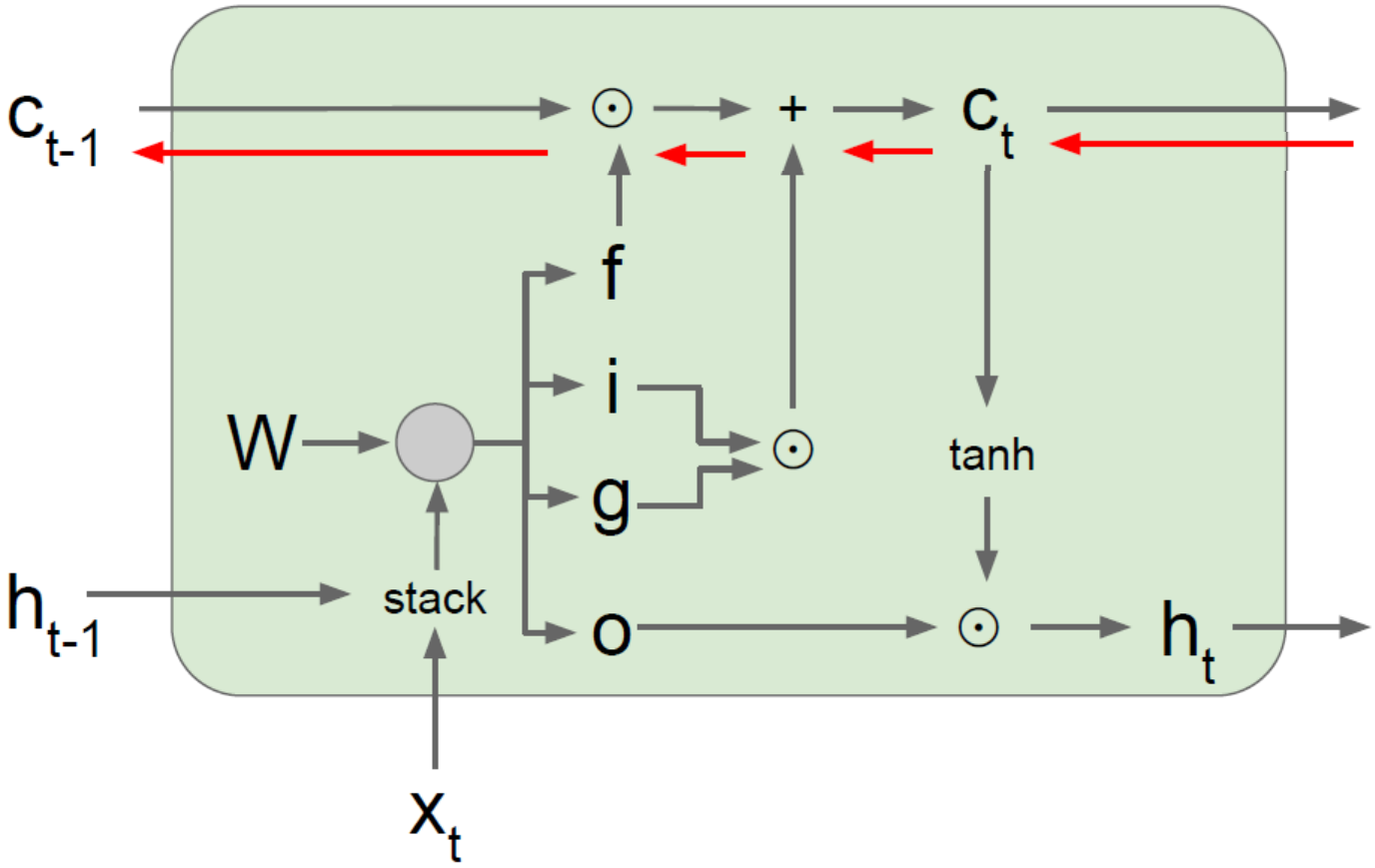
LSTM. Gradient Flow

- Что будет если forget_gate=1 всегда?
- Как надо инициализировать bias_forget_gate?

$$\boldsymbol{c}_t = \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{c}'_t.$$

$$\frac{\partial \boldsymbol{c}_t}{\partial \boldsymbol{c}_{t-1}} = 1.$$

LSTM. Gradient Flow



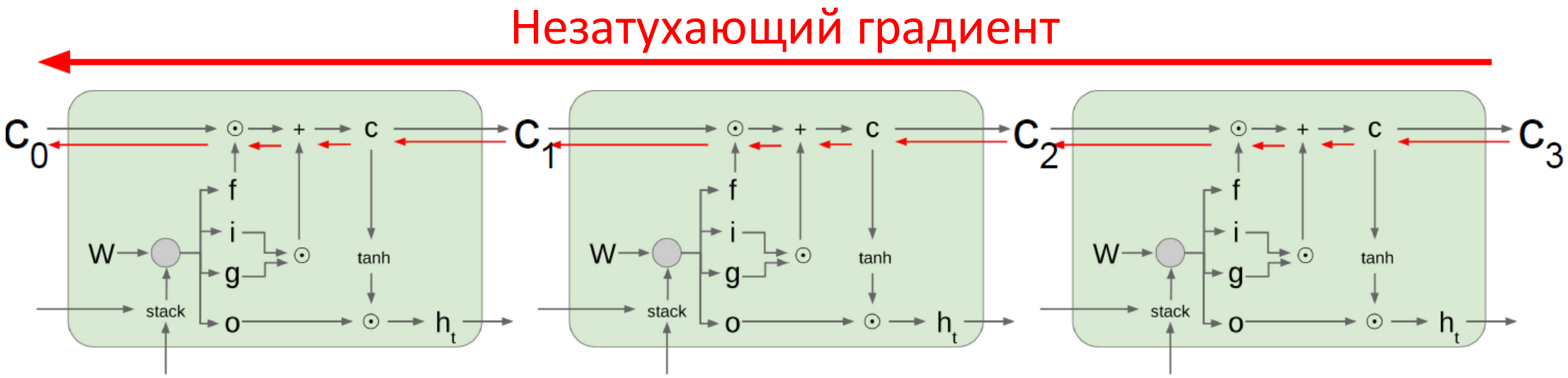
Обратный проход от c_t до c_{t-1} перемножаются только с f без матрицы W

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

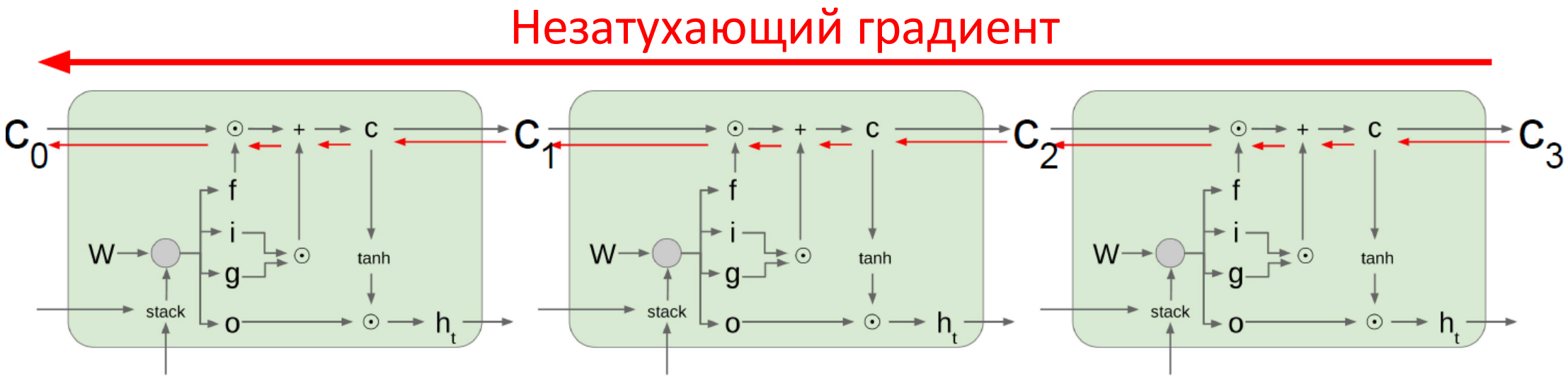
$$c_t = f \odot c_{t-1} + i \odot g$$

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

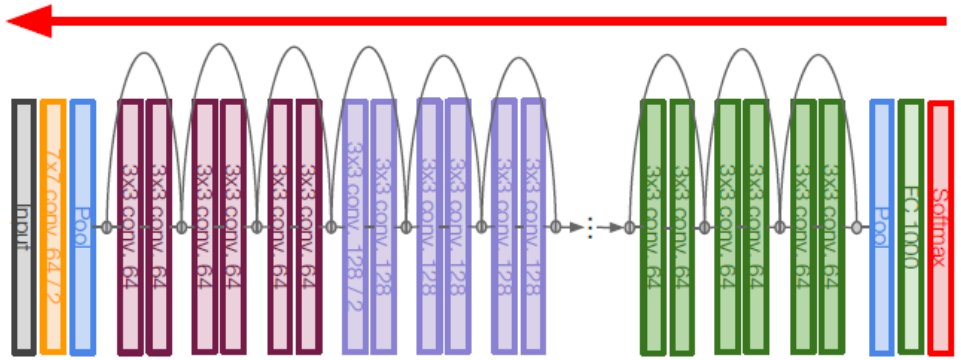
LSTM. Gradient Flow



LSTM. Gradient Flow

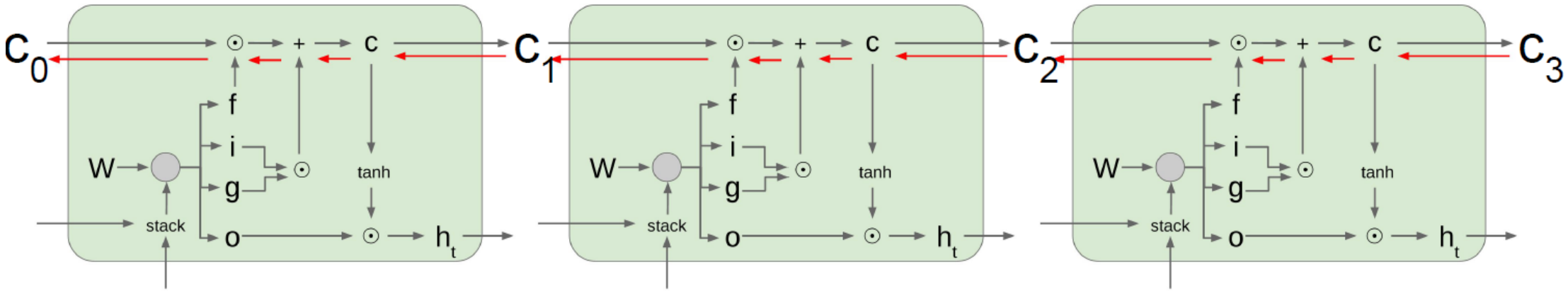


ResNet

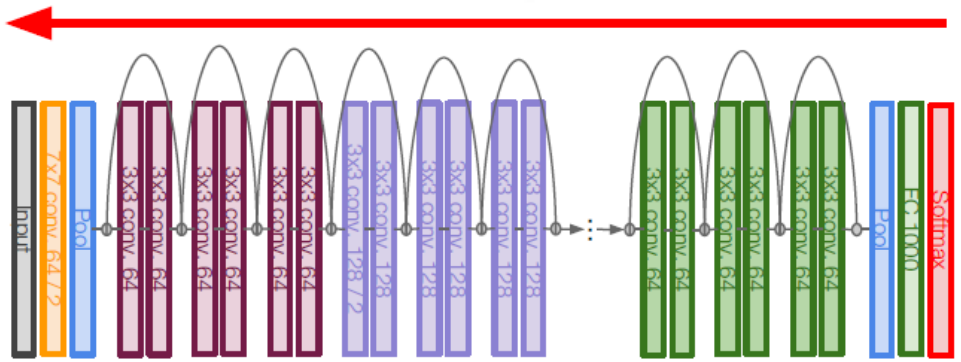


LSTM. Gradient Flow

Незатухающий градиент



ResNet



Highway Networks

$$g = T(x, W_T)$$

$$y = g \odot H(x, W_H) + (1 - g) \odot x$$

Srivastava et al, “Highway Networks”, ICML DL Workshop 2015

Long Short Term Memory (LSTM)

$$
\begin{aligned}
\boldsymbol{c}'_t &= \tanh\left(W_{xc}\boldsymbol{x}_t + W_{hc}\boldsymbol{h}_{t-1} + \boldsymbol{b}_{c'}\right) && \textit{candidate cell state} \\
\boldsymbol{i}_t &= \sigma\left(W_{xi}\boldsymbol{x}_t + W_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i\right) && \textit{input gate} \\
\boldsymbol{f}_t &= \sigma\left(W_{xf}\boldsymbol{x}_t + W_{hf}\boldsymbol{h}_{t-1} + \boldsymbol{b}_f\right) && \textit{forget gate} \\
\boldsymbol{o}_t &= \sigma\left(W_{xo}\boldsymbol{x}_t + W_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o\right) && \textit{output gate} \\
\boldsymbol{c}_t &= \boldsymbol{f}_t \odot \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{c}'_t, && \textit{cell state} \\
\boldsymbol{h}_t &= \boldsymbol{o}_t \odot \tanh(\boldsymbol{c}_t) && \textit{block output}
\end{aligned}
$$

$$y_t = W_{hy}\, h_t$$

LSTM – peepholes («замочные скважины»)

- Зависят ли gate от состояние ячейки памяти (cell)?

$$\boldsymbol{i}_t = \sigma\left(W_{xi}\boldsymbol{x}_t + W_{hi}\boldsymbol{h}_{t-1} + W_{pi}\boldsymbol{c}_{t-1} + \boldsymbol{b}_i\right)$$
$$\boldsymbol{f}_t = \sigma\left(W_{xf}\boldsymbol{x}_t + W_{hf}\boldsymbol{h}_{t-1} + W_{pf}\boldsymbol{c}_{t-1} + \boldsymbol{b}_f\right)$$
$$\boldsymbol{o}_t = \sigma\left(W_{xo}\boldsymbol{x}_t + W_{ho}\boldsymbol{h}_{t-1} + W_{po}\boldsymbol{c}_{t-1} + \boldsymbol{b}_o\right)$$

Vanilla RNN – как ее получить из LSTM?

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

$$y_t = W_{hy}\, h_t$$

LSTM – важные моменты

- Внутренняя ячейка памяти – cell
- Забывающий гейт (forget gate)
- Выходной гейт (output gate)
- Незатухающая ошибка по памяти
- Функция активации выхода не дает градиентам

GRU RNN

GRU [*Learning phrase representations using rnn encoder-decoder for statistical machine translation*, Cho et al. 2014]

$$
\begin{aligned}
\boldsymbol{u}_t &= \sigma(W_{xu}\boldsymbol{x}_t + W_{hu}\boldsymbol{h}_{t-1} + \boldsymbol{b}_u), \\
\boldsymbol{r}_t &= \sigma(W_{xr}\boldsymbol{x}_t + W_{hr}\boldsymbol{h}_{t-1} + \boldsymbol{b}_r), \\
\boldsymbol{h}'_t &= \tanh(W_{xh'}\boldsymbol{x}_t + W_{hh'}(\boldsymbol{r}_t \odot \boldsymbol{h}_{t-1})), \\
\boldsymbol{h}_t &= (1 - \boldsymbol{u}_t) \odot \boldsymbol{h}'_t + \boldsymbol{u}_t \odot \boldsymbol{h}_{t-1}.
\end{aligned}
$$

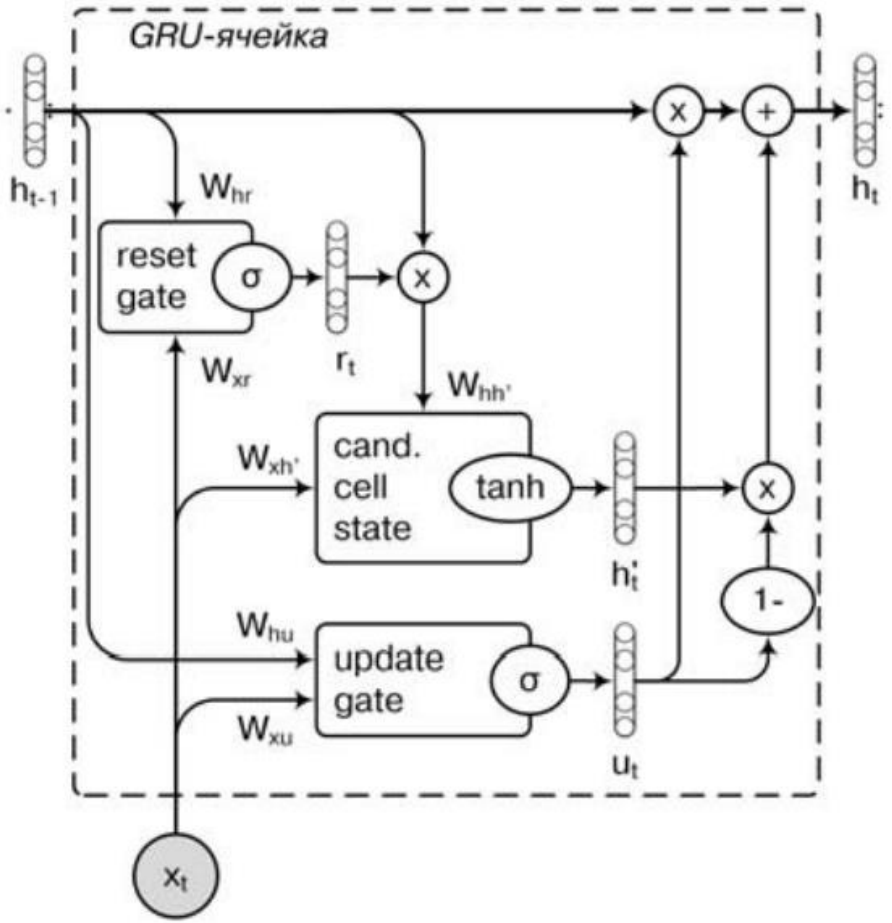
GRU – gated recurrent unit

- Совмещаем выходные и забывающий гейты – их заменяет update_gate (u)
- Совмещаем hidden_state(h) и cell_state(c) – объединяем их
- Добавляем reset_gate

GRU – gated recurrent unit

- reset_gate – определяет как объединить новый вход (x) с имеющимся состояним (h)
- update_gate – какую часть памяти оставить неизменной
- hiddent_state опять имеет линейную связь для градиентов через update_gate

GRU – gated recurrent unit



Vanilla RNN – как ее получить из GRU?

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

$$y_t = W_{hy}\, h_t$$

Использованные материалы

- Книга «**Николенко, Кадурин, Архангельская: Глубокое обучение. Погружение в мир нейронных сетей»**