Vanishing and exploding gradients

RECURRENT NEURAL NETWORKS (RNNS) FOR LANGUAGE MODELING WITH KERAS

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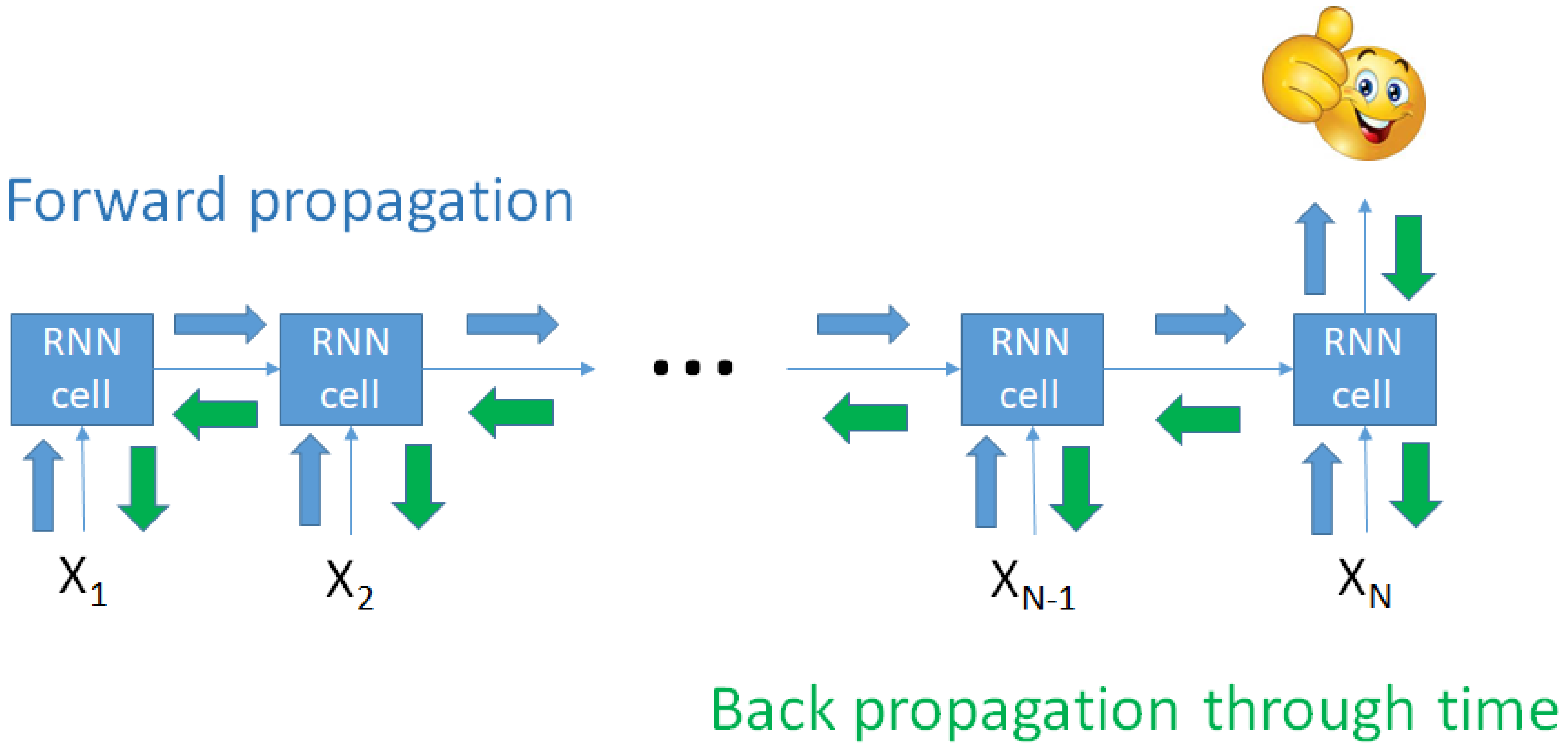
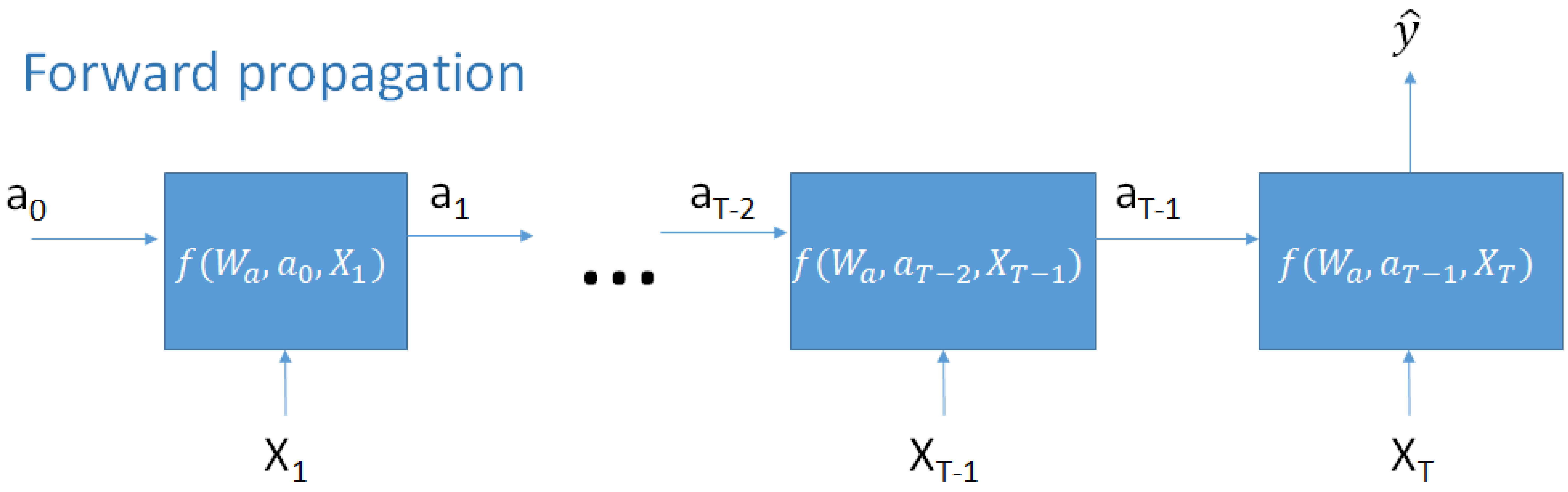
Training RNN models



Forward propagation

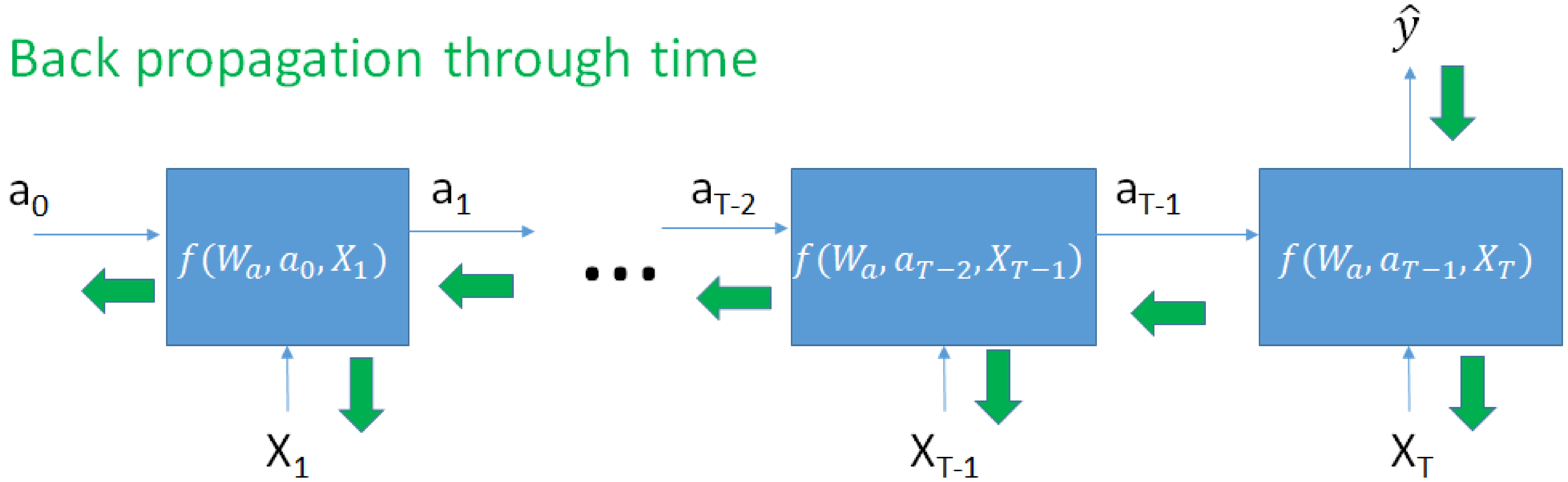


Example:

$$a_2 = f(W_a, a_1, x_2)$$

$$= f(W_a, f(W_a, a_0, x_1), x_2)$$

Back propagation through time



Remember that:

$$a_T = f(W_a, a_{T-1}, x_T)$$

a_T also depends on a_{T-1} which depends on a_{T-2} and W_a, and so on !

BPTT continuation

Computing derivatives leads to

$$\frac{\partial a_t}{\partial W_a} = (W_a)^{t-1} g(X)$$

- $(W_a)^{t-1}$ **can converge to 0**
- **or diverge to** $+\infty$**!**

Solutions to the gradient problems

Some solutions are known:

Exploding gradients

- Gradient clipping / scaling

Vanishing gradients

- Better initialize the matrix W
- Use regularization
- Use ReLU instead of tanh / sigmoid / softmax
- **Use LSTM or GRU cells!**

Let's practice!

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GRU and LSTM cells

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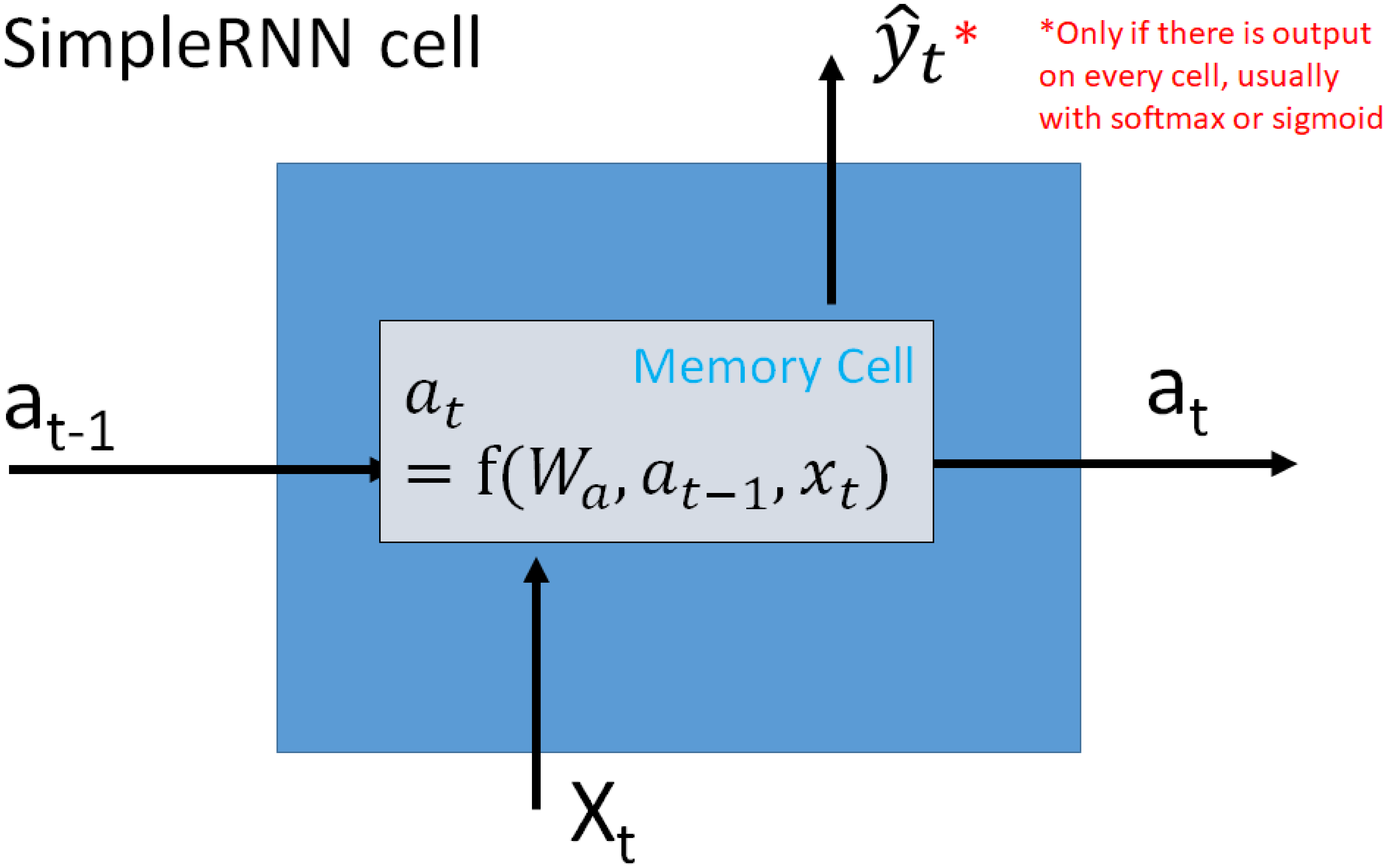
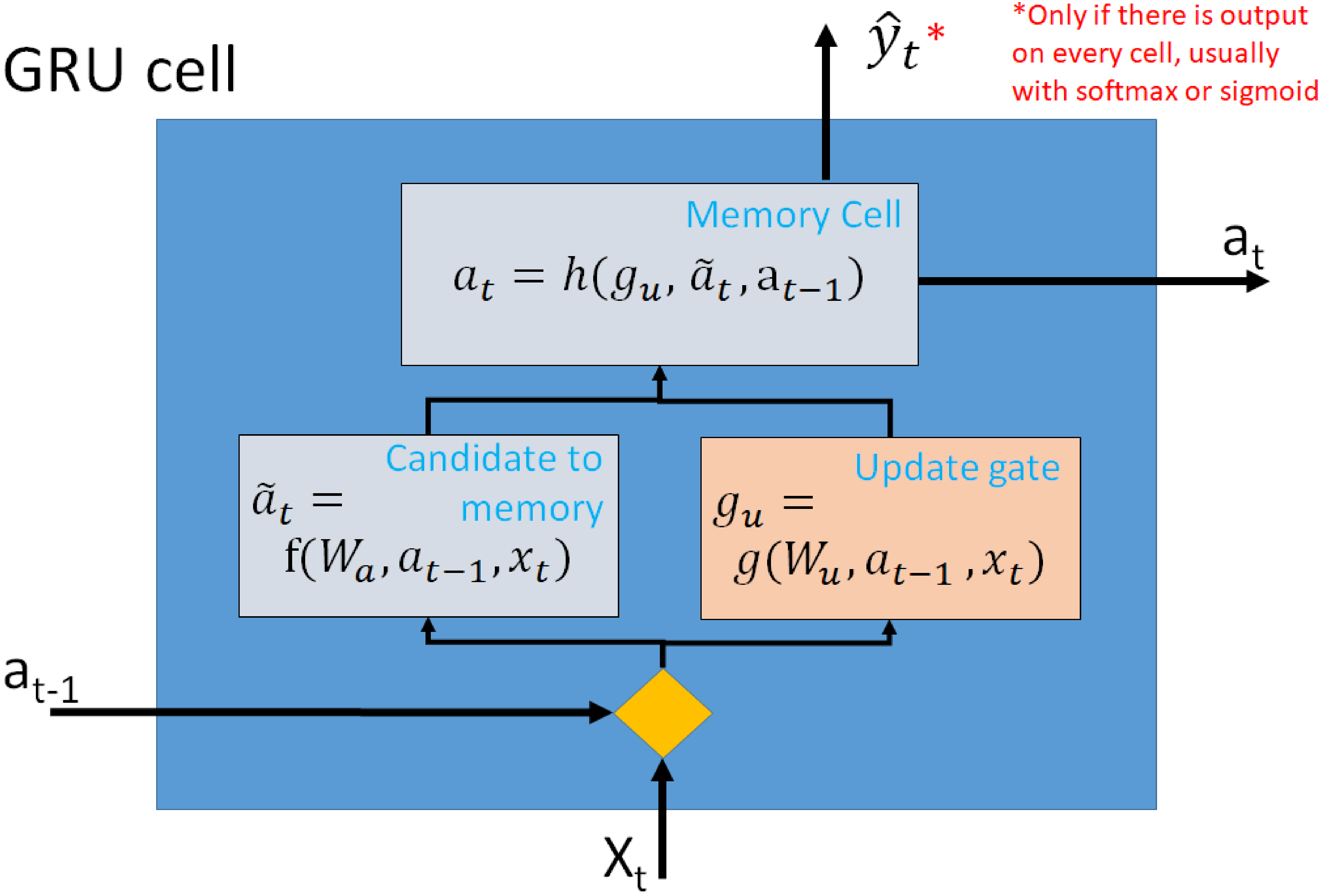
SimpleRNN cell

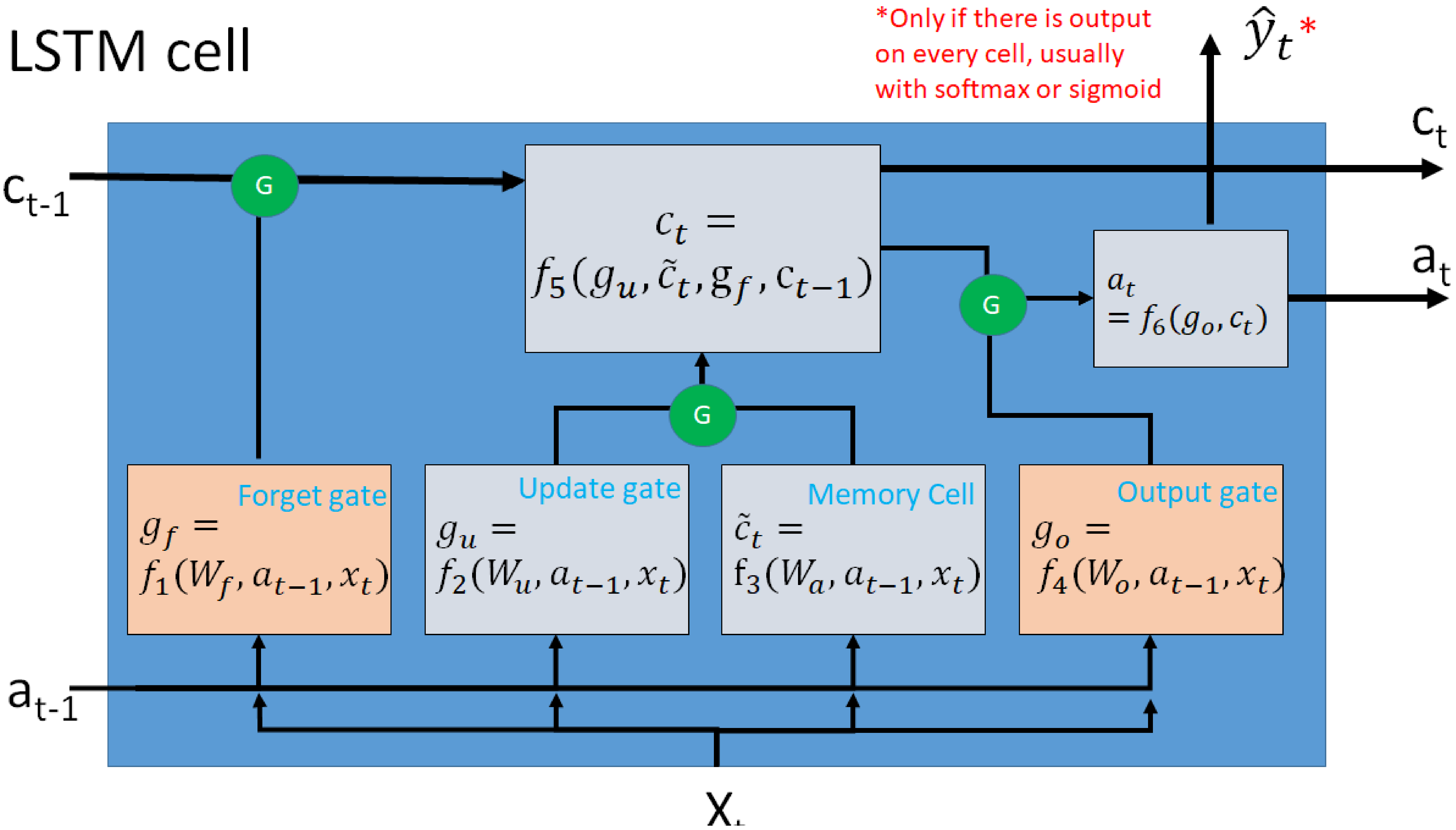


GRU cell



$\hat{y}_t$*
*Only if there is output on every cell, usually with softmax or sigmoid
Memory Cell
$a_t = h(g_u, \tilde{a}_t, a_{t-1})$
a_t
Candidate to memory
$\tilde{a}_t = f(W_a, a_{t-1}, x_t)$
Update gate
$g_u = g(W_u, a_{t-1}, x_t)$
a_{t-1}
X_t

LSTM cell



*Only if there is output on every cell, usually with softmax or sigmoid
$\hat{y}_t$*
c_t
a_t
c_{t-1}
G
$c_t = f_5(g_u, \tilde{c}_t, g_f, c_{t-1})$
G
$a_t = f_6(g_o, c_t)$
G
G
Forget gate
$g_f = f_1(W_f, a_{t-1}, x_t)$
Update gate
$g_u = f_2(W_u, a_{t-1}, x_t)$
Memory Cell
$\tilde{c}_t = f_3(W_a, a_{t-1}, x_t)$
Output gate
$g_o = f_4(W_o, a_{t-1}, x_t)$
a_{t-1}
x_t

No more vanishing gradients

- The `simpleRNN` cell can have gradient problems.
  - The weight matrix power t multiplies the other terms
- `GRU` and `LSTM` cells don't have vanishing gradient problems
  - Because of their gates
  - Don't have the weight matrices terms multiplying the rest
  - Exploding gradient problems are easier to solve

Usage in keras

```
# Import the layers
from tensorflow import keras
from tensorflow.keras.layers import GRU, LSTM
```

```
# Add the layers to a model
model.add(GRU(units=128, return_sequences=True, name='GRU layer'))
model.add(LSTM(units=64, return_sequences=False, name='LSTM layer'))
```

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The Embedding layer

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Why embeddings

Advantages:

- Reduce the dimension

```
one_hot = np.array((N, 100000))
embedd = np.array((N, 300))
```

- Dense representation
  - `king - man + woman = queen`
- Transfer learning

Disadvantages:

- Lots of parameters to train: training takes longer

How to use in keras

In keras:

```
from tensorflow.keras.layers import Embedding
model = Sequential()

# Use as the first layer
model.add(Embedding(input_dim=100000,
                    output_dim=300,
                    trainable=True,
                    embeddings_initializer=None,
                    input_length=120))
```

Transfer learning

Transfer learning for language models

- GloVE
- word2vec
- BERT

In keras:

```
from tensorflow.keras.initializers import Constant
model.add(Embedding(input_dim=vocabulary_size,
                    output_dim=embedding_dim,
                    embeddings_initializer=Constant(pre_trained_vectors))
```

Using GloVE pre-trained vectors

Official site: `https://nlp.stanford.edu/projects/glove/`

```
# Get hte GloVE vectors
def get_glove_vectors(filename="glove.6B.300d.txt"):
    # Get all word vectors from pre-trained model
    glove_vector_dict = {}
    with open(filename) as f:
        for line in f:
            values = line.split()
            word = values[0]
            coefs = values[1:]
            glove_vector_dict[word] = np.asarray(coefs, dtype='float32')

    return glove_vector_dict
```

Using the GloVE on a specific task

```
# Filter GloVE vectors to specific task
def filter_glove(vocabulary_dict, glove_dict, wordvec_dim=300):
    # Create a matrix to store the vectors
    embedding_matrix = np.zeros((len(vocabulary_dict) + 1, wordvec_dim))
    for word, i in vocabulary_dict.items():
        embedding_vector = glove_dict.get(word)
        if embedding_vector is not None:
            # words not found in the glove_dict will be all-zeros.
            embedding_matrix[i] = embedding_vector

    return embedding_matrix
```

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Sentiment classification revisited

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Previous results

We had bad results with our initial model.

```
model = Sequential()
model.add(SimpleRNN(units=16, input_shape=(None, 1)))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='sgd', metrics=['accuracy'])
model.evaluate(x_test, y_test)
```

```
$[0.6991182165145874, 0.495]
```

Improving the model

To improve the model's performance, we can:

- Add the embedding layer
- Increase the number of layers
- Tune the parameters
- Increase vocabulary size
- Accept longer sentences with more memory cells

Avoiding overfitting

RNN models can overfit

- Test different batch sizes.
- Add `Dropout` layers.
- Add `dropout` and `recurrent_dropout` parameters on RNN layers.

```
# removes 20% of input to add noise
model.add(Dropout(rate=0.2))
# Removes 10% of input and memory cells respectively
model.add(LSTM(128, dropout=0.1, recurrent_dropout=0.1))
```

Extra: Convolution Layer

Not in the scope:

```
model.add(Embedding(vocabulary_size, wordvec_dim, ...))
model.add(Conv1D(num_filters=32, kernel_size=3, padding='same'))
model.add(MaxPooling1D(pool_size=2))
```

- Convolution layer do feature selection on the embedding vector
- Achieves state-of-the-art results in many NLP problems

One example model

```
model = Sequential()
model.add(Embedding(  vocabulary_size, wordvec_dim, trainable=True,
                      embeddings_initializer=Constant(glove_matrix),
                      input_length=max_text_len, name="Embedding"))
model.add(Dense(wordvec_dim, activation='relu', name="Dense1"))
model.add(Dropout(rate=0.25))
model.add(LSTM(64, return_sequences=True, dropout=0.15, name="LSTM"))
model.add(GRU(64, return_sequences=False, dropout=0.15, name="GRU"))
model.add(Dense(64, name="Dense2"))
model.add(Dropout(rate=0.25))
model.add(Dense(32, name="Dense3"))
model.add(Dense(1, activation='sigmoid', name="Output"))
```

Let's practice!