Recurrent Neural Networks & Long Short-Termed Memory

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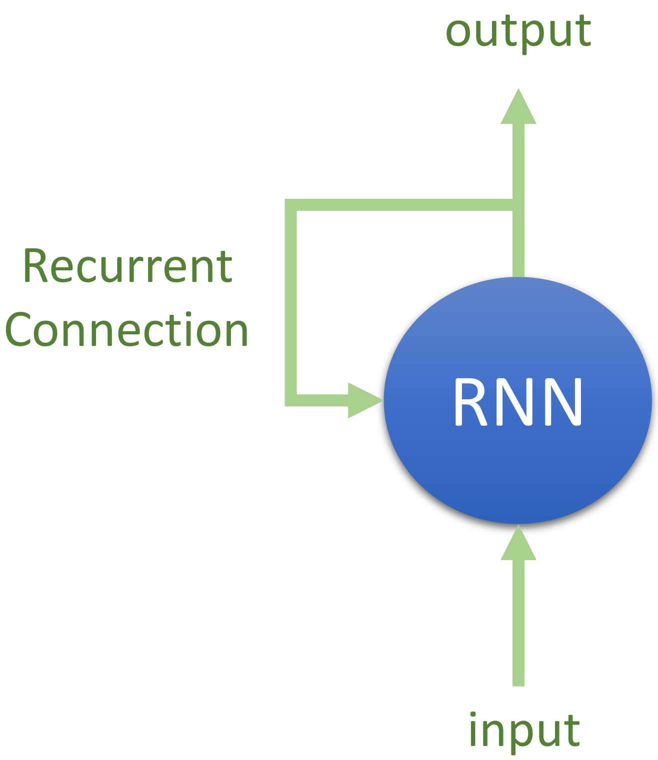
2021/11/4

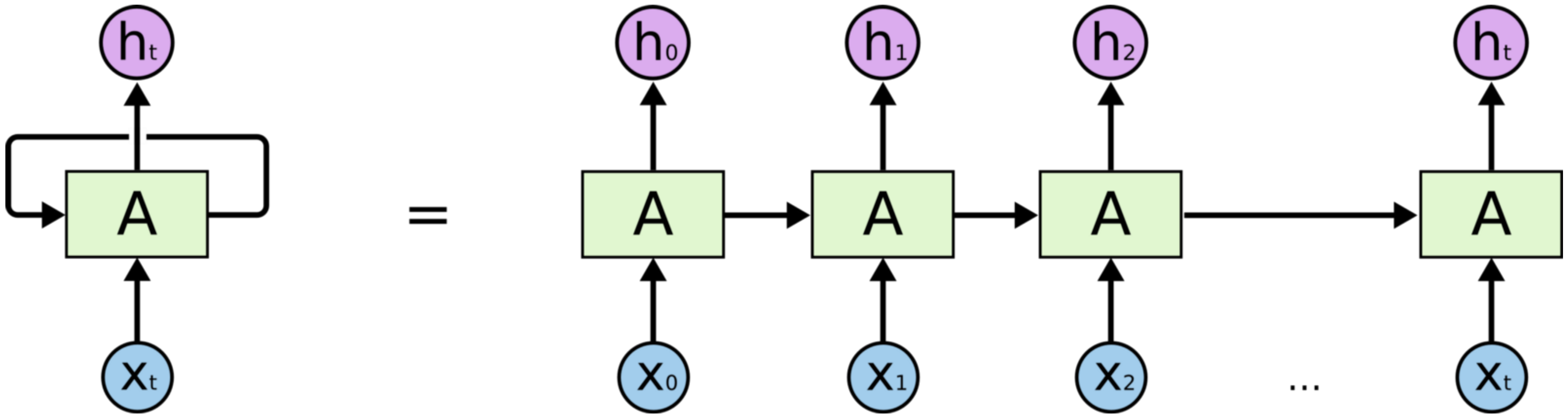
Recurrent Neural Networks (RNN)

- Feedforward networks don't consider temporal states
- RNN has a loop to "memorize" information



Unroll the RNN Loop

- Effective for speech recognition, language modeling, translation



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

Pseudo RNN

$$y_t = \sigma_h(Wx_t + Uy_{t-1} + b)$$

```
# Pseudo RNN
state_t = 0
for input_t in input_sequence:
    output_t = f(input_t, state_t)
    state_t = output_t


# Pseudo RMN with activation function
# y_t = W*x_t + U*S_t + b
state_t = 0
for input_t in input_sequence:
    output_t = activation(dot(W, input_t) + dot(U, state_t) + b)
    state_t = output_t
```

RNN using Numpy

Number of timesteps in the input sequence

Dimensionality of the input feature space

Dimensionality of the output feature space

Input data: random noise for the sake of the example

Initial state: an all-zero vector

Creates random weight matrices

input_t is a vector of shape (input_features,).

```
import numpy as np

timesteps = 100
input_features = 32
output_features = 64

inputs = np.random.random((timesteps, input_features))

state_t = np.zeros((output_features,))

W = np.random.random((output_features, input_features))
U = np.random.random((output_features, output_features))
b = np.random.random((output_features,))

successive_outputs = []
for input_t in inputs:
    output_t = np.tanh(np.dot(W, input_t) + np.dot(U, state_t) + b)

    successive_outputs.append(output_t)

    state_t = output_t

final_output_sequence = np.concatenate(successive_outputs, axis=0)
```

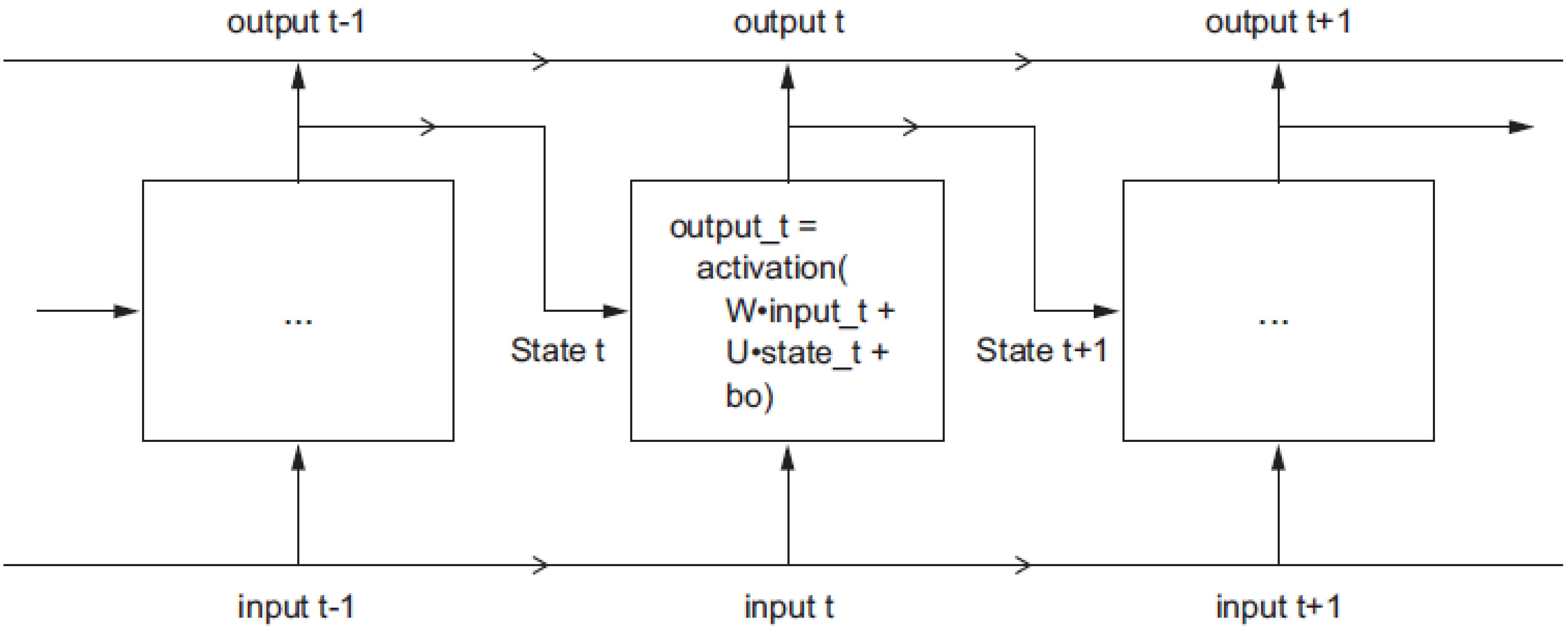
Stores this output in a list

The final output is a 2D tensor of shape (timesteps, output_features).

Combines the input with the current state (the previous output) to obtain the current output

Updates the state of the network for the next timestep

Unroll RNN


output t-1
output t
output t+1
...
State t
output_t =
activation(
W•input_t +
U•state_t +
bo)
State t+1
...
input t-1
input t
input t+1

Recurrent Layer in Keras

- Simple RNN

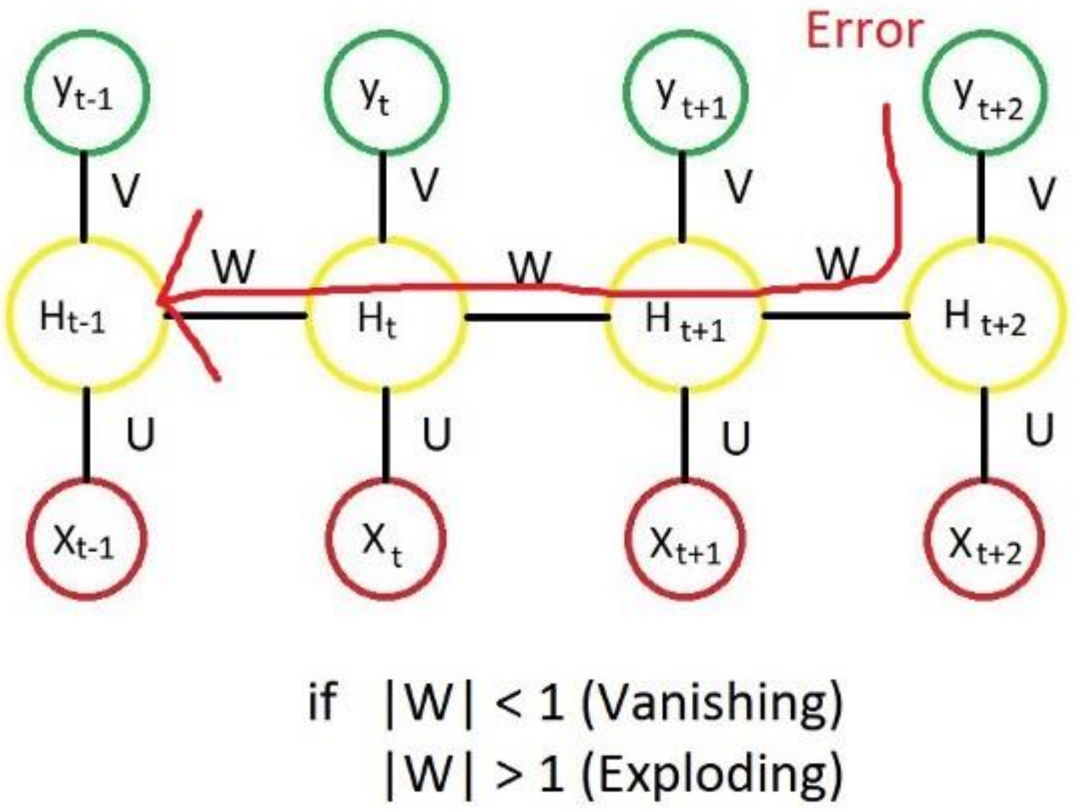
```
from keras.models import Sequential
from keras.layers import Embedding, SimpleRNN

model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32, return_sequences=True))
model.add(SimpleRNN(32))
model.summary()
```

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_24 (Embedding)     (None, None, 32)          320000
_________________________________________________________________
simplernn_12 (SimpleRNN)     (None, None, 32)          2080
_________________________________________________________________
simplernn_13 (SimpleRNN)     (None, None, 32)          2080
_________________________________________________________________
simplernn_14 (SimpleRNN)     (None, None, 32)          2080
_________________________________________________________________
simplernn_15 (SimpleRNN)     (None, 32)                2080
=================================================================
Total params: 328,320
Trainable params: 328,320
Non-trainable params: 0
```

$$= 32 \times (\underbrace{32}_{W} + \underbrace{32}_{U} + \underbrace{1}_{b})$$

Vanishing and Exploding Gradient Problems

- Hochreiter (1991) [German] and Bengio, et al. (1994)

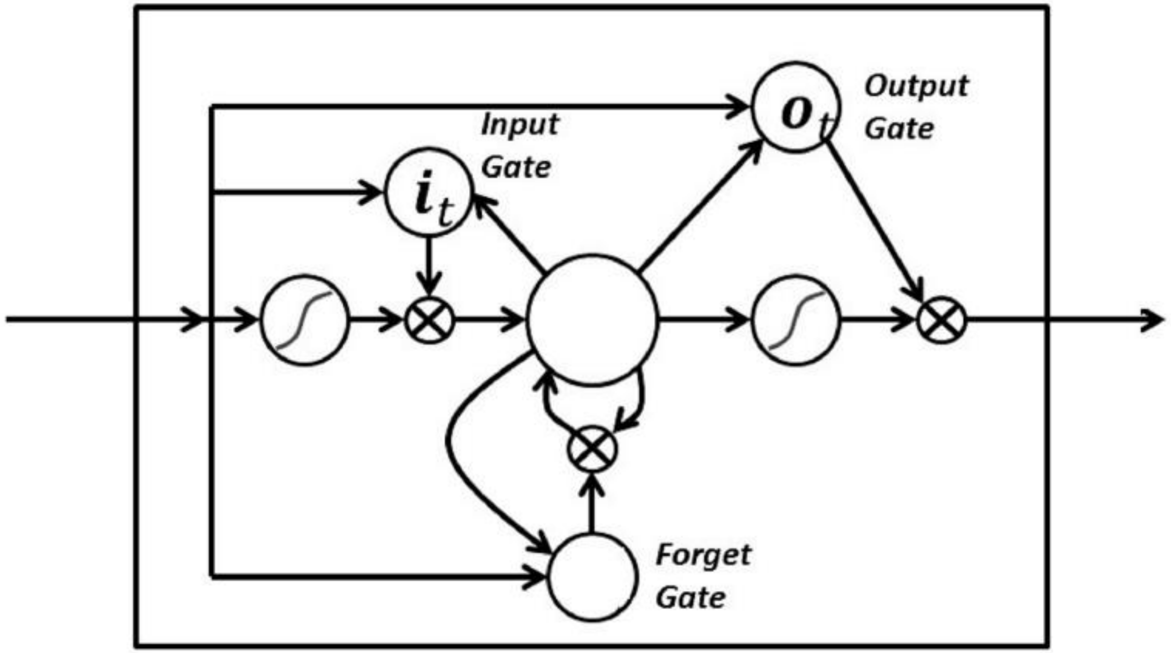


https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

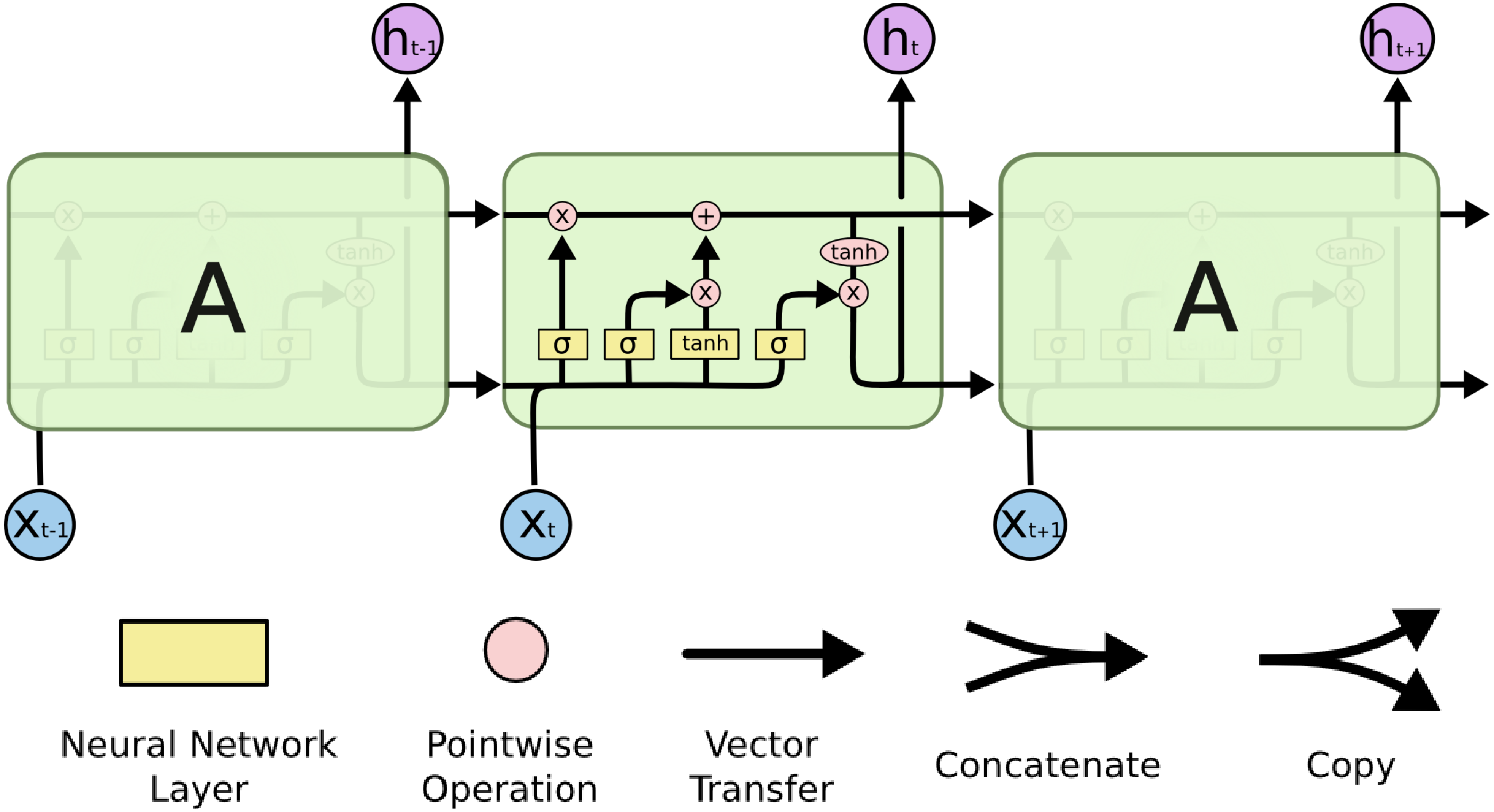
Long Short-Term Memory (LSTM)

- **Input gate**: control when to let new input in
- **Forget gate**: delete the trivial information
- **Output gate**: let the info impact the output at the current time step

[Hochreiter & Schmidhuber (1997)]



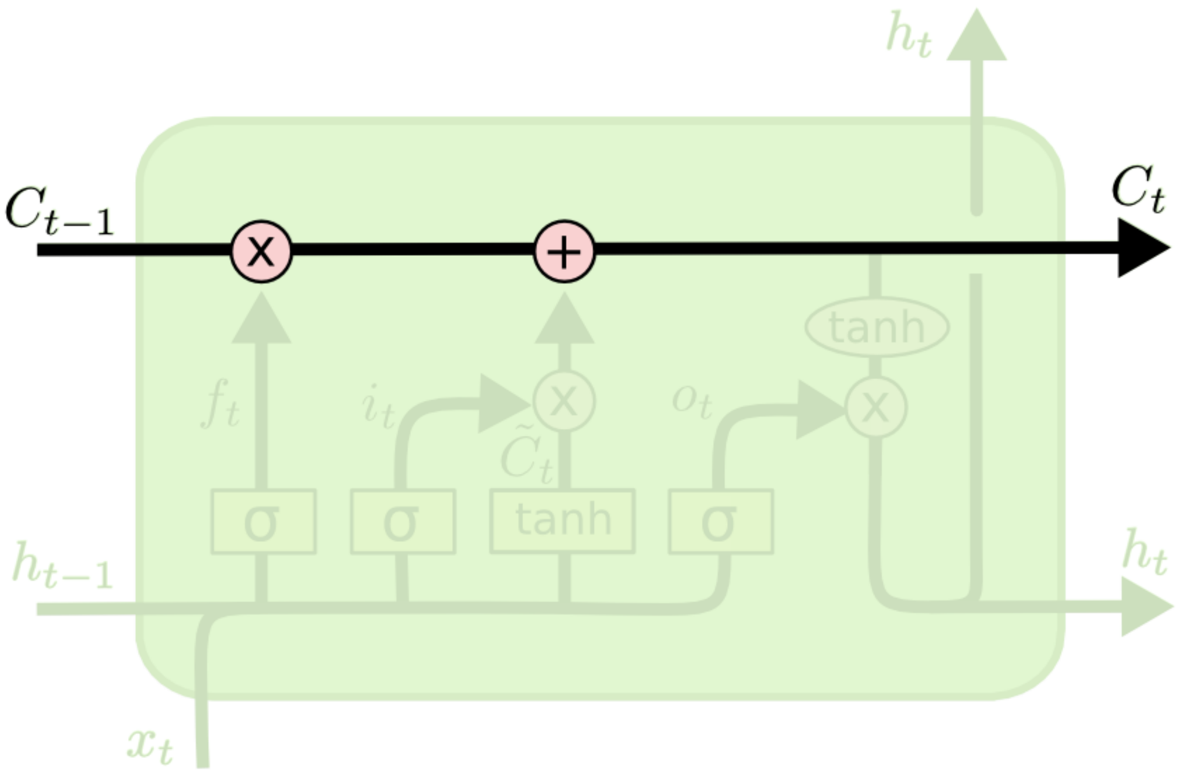
Long Short-Term Memory (LSTM)

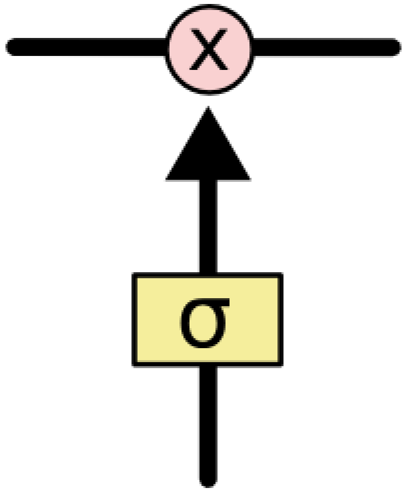


https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Core Idea of LSTM

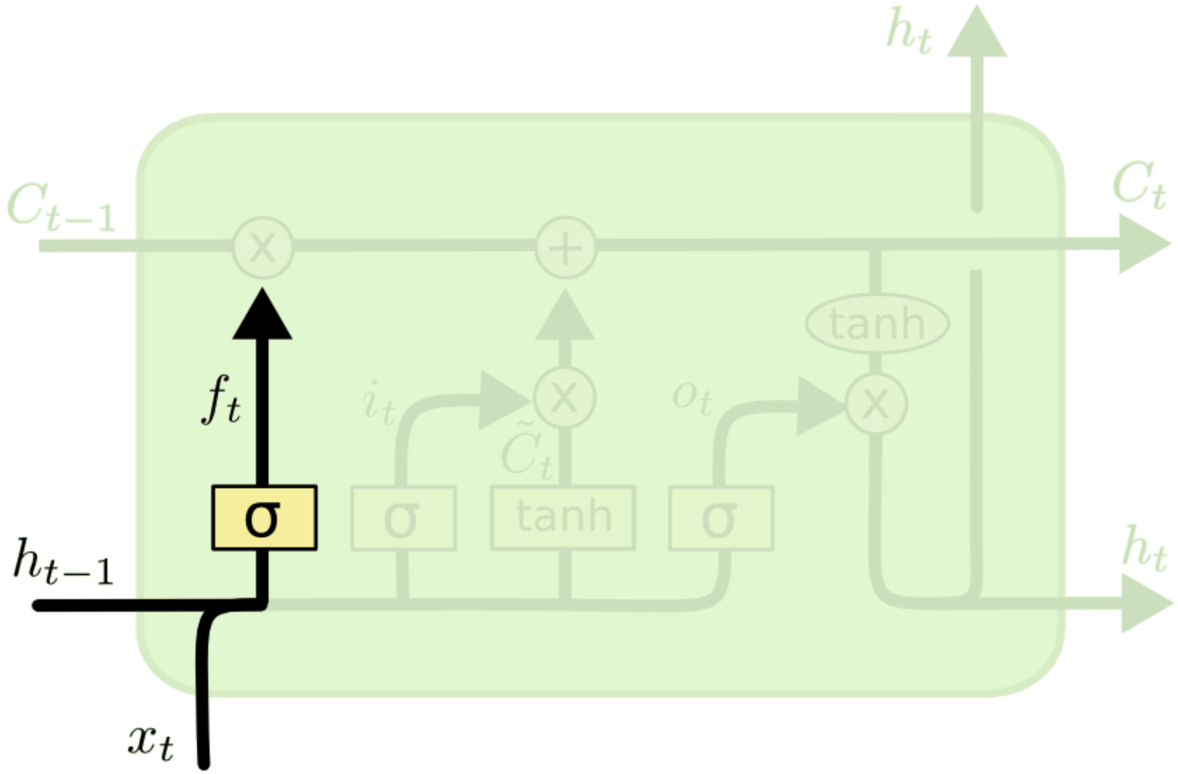
- Cell State C_t : allow information flow unchanged





LSTM Step-by-Step (4-1)

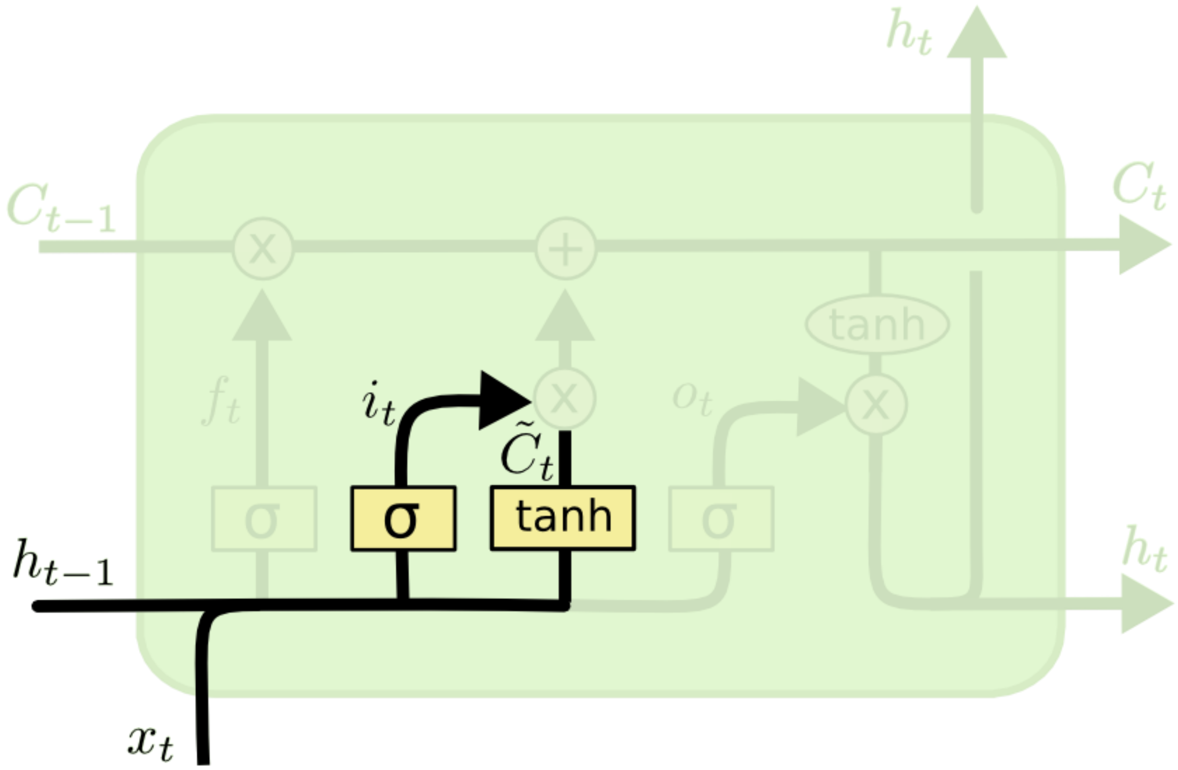
- Decide if to throw away old cell state information C_{t-1}



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

LSTM Step-by-Step (4-2)

- Decide what information to be stored in current cell state C_t

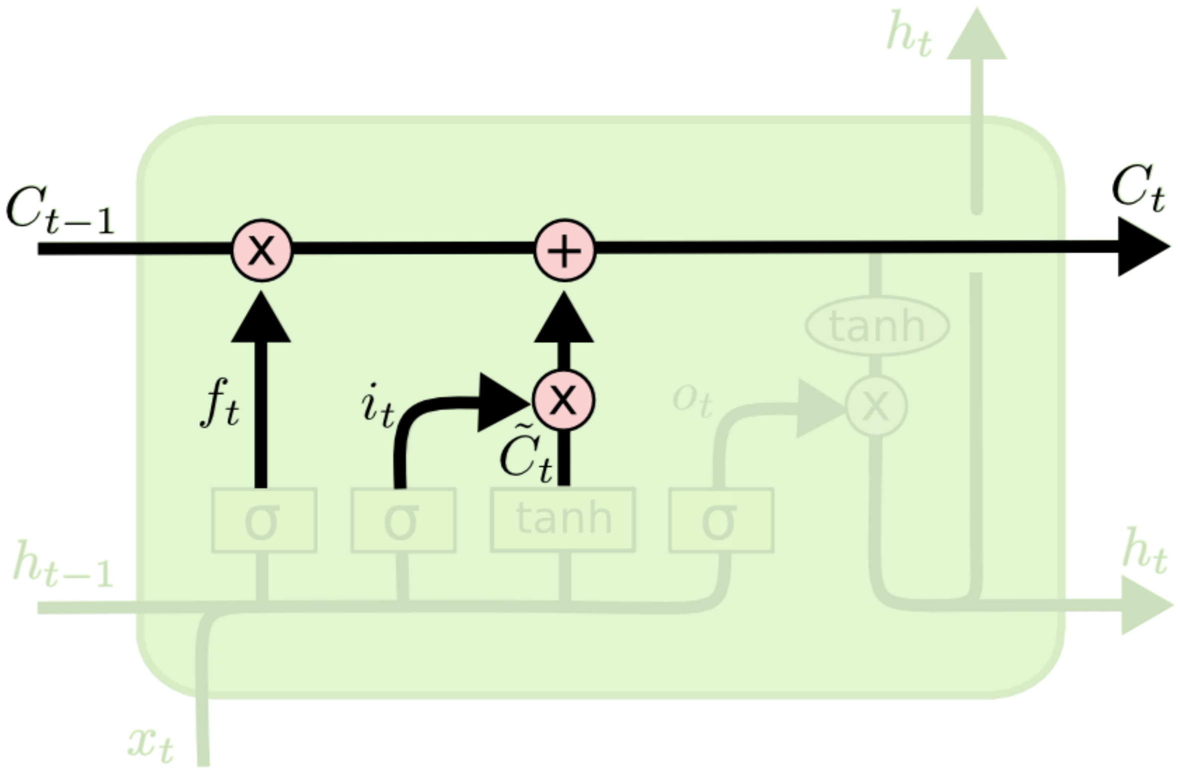


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

LSTM Step-by-Step (4-3)

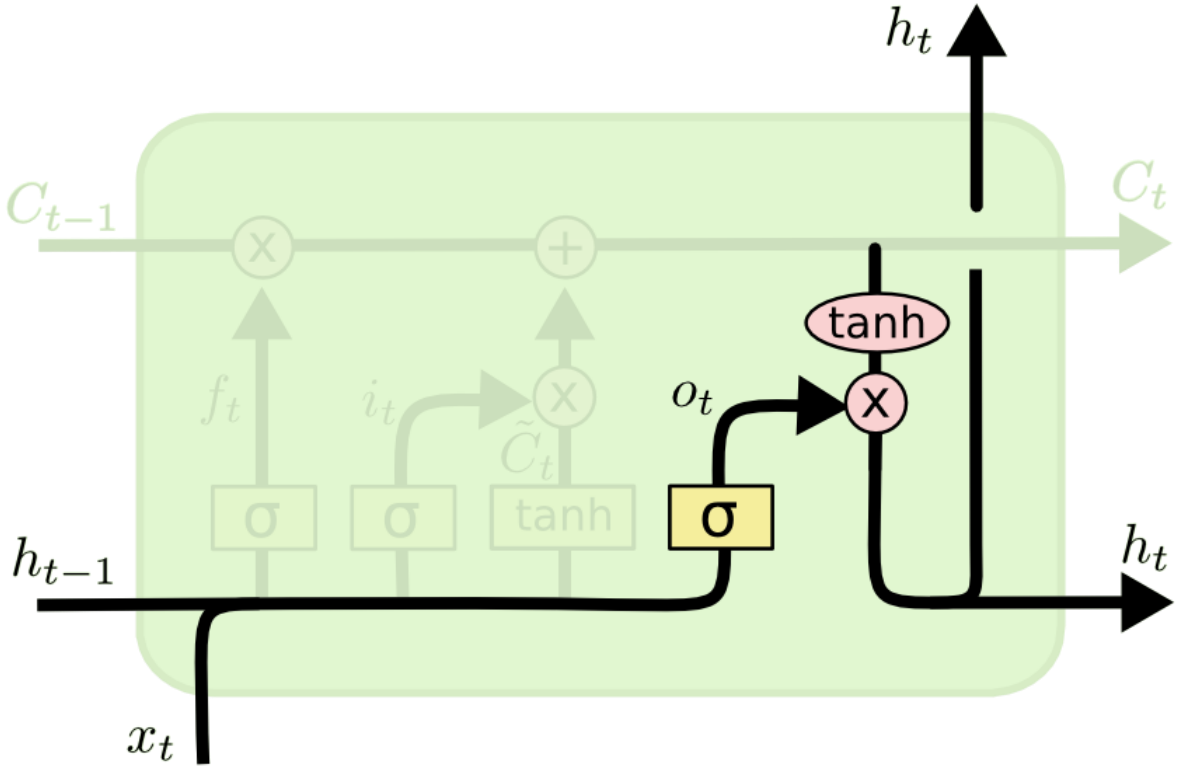
- Update old cell state $C_{t\text{-}1}$ into current C_t

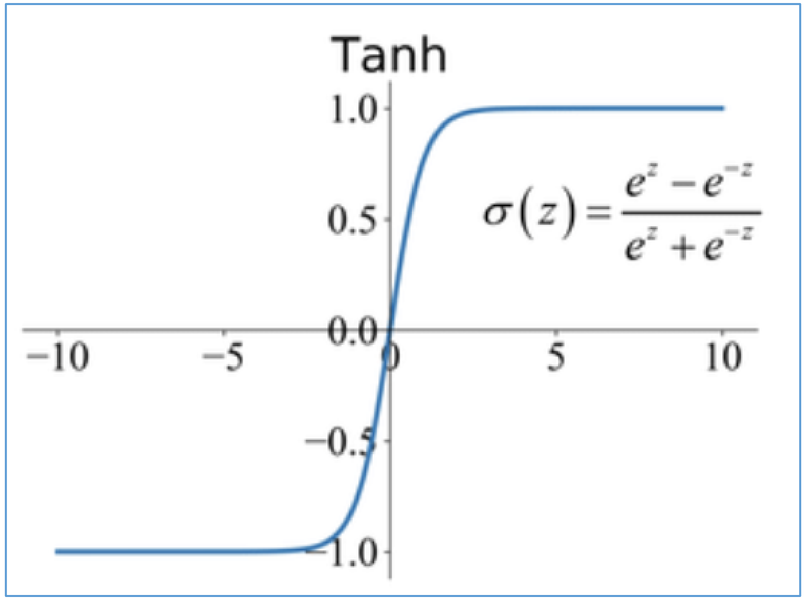


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

LSTM Step-by-Step (4-4)

- Decide what to output





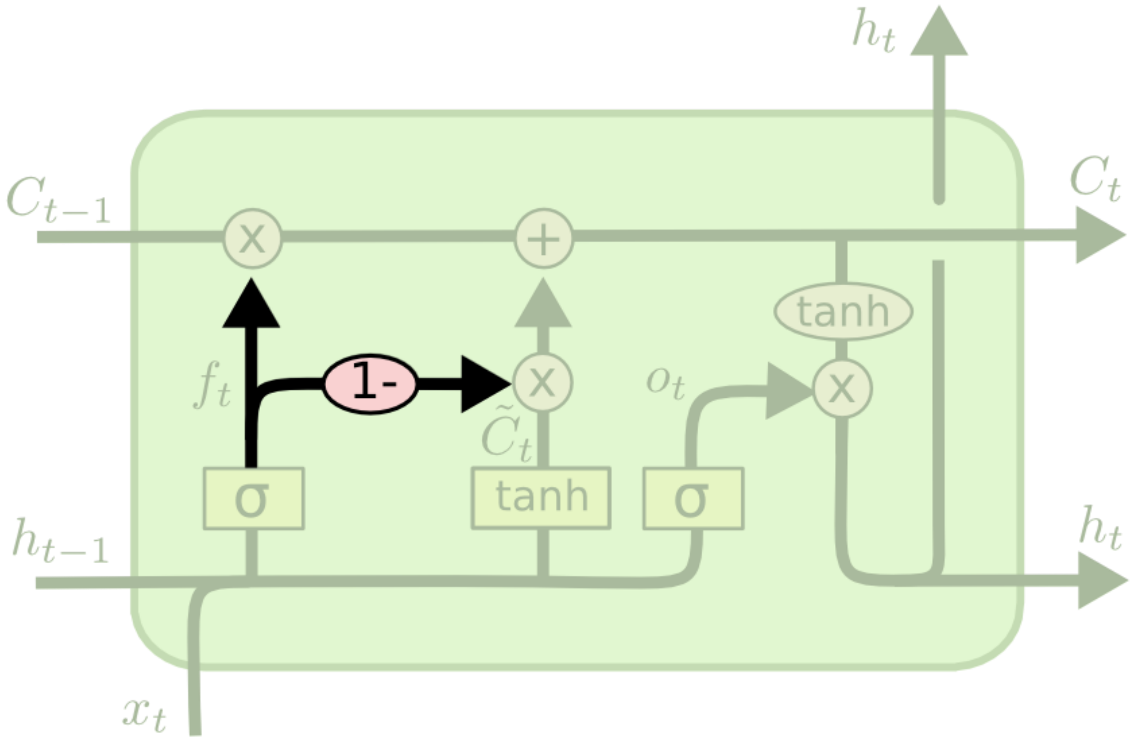
https://www.researchgate.net/profile/Junxi-Feng

$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Variants of LSTM

- Couple forget gate and input gate

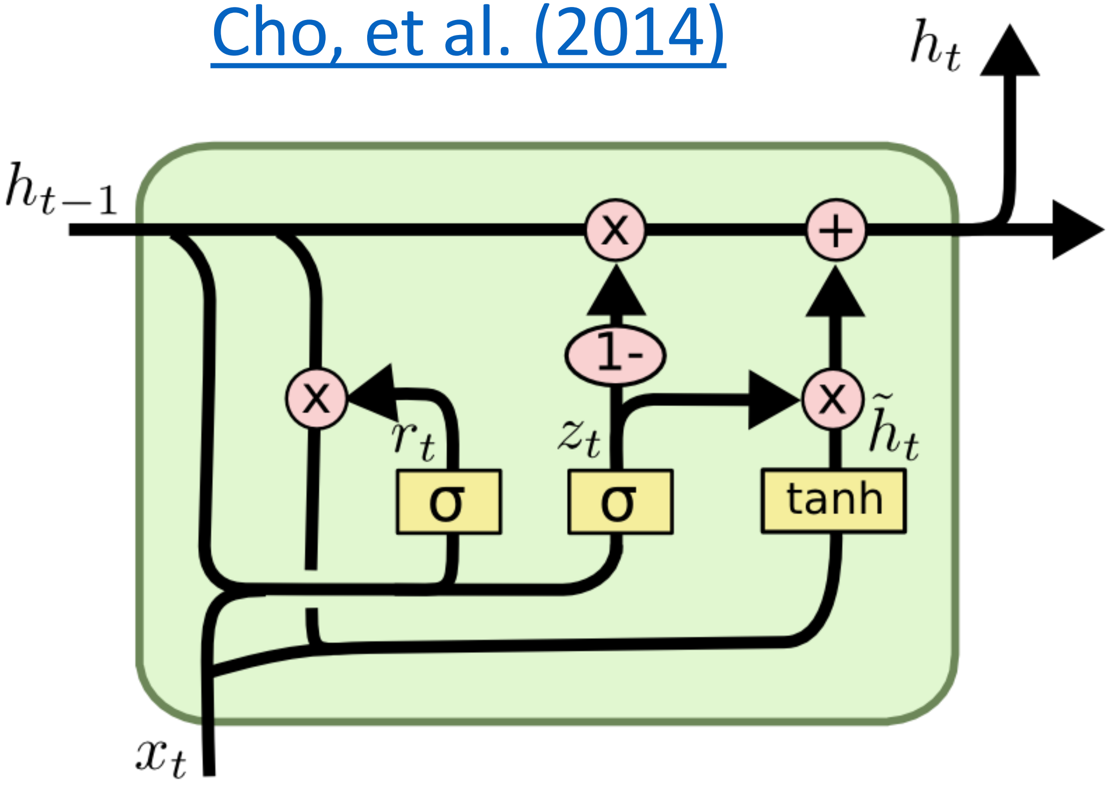


$$C_t = f_t * C_{t-1} + (1 - \boldsymbol{f_t}) * \tilde{C}_t$$

Gated Recurrent Unit (GRU)

- Combine the forget and input gate into a single "update gate."
- Merge the hidden state and cell state

Cho, et al. (2014)



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Using LSTM in Keras

```
from keras.layers import LSTM

model = Sequential()
model.add(Embedding(max_words, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop',
                loss='binary_crossentropy',
                metrics=['acc'])
history = model.fit(x_train, y_train,
                epochs=10,
                batch_size=128,
                validation_split=0.2)
```

Advanced Use of RNN

- *Recurrent dropout*
  - Use dropout to fight overfitting in recurrent layers
- *Stacking recurrent layers*
  - This increases the representational power of the network (at the cost of higher computational loads)
- *Bidirectional recurrent layers*
  - These present the same information to a recurrent network in different ways, increasing accuracy and mitigating forgetting issues

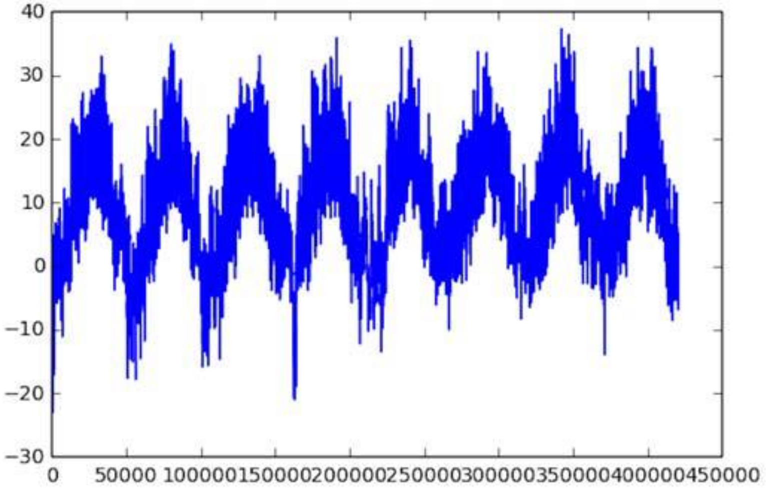
Temperature-forecasting Problem

- Measure 14 features every 10 minutes from 2009 – 2016 in Jena, Germany

["Date Time",
"p (mbar)",
"T (degC)",
"Tpot (K)",
"Tdew (degC)",
"rh (%)",
"VPmax (mbar)",
"VPact (mbar)",
"VPdef (mbar)",
"sh (g/kg)",
"H2OC (mmol/mol)",
"rho (g/m**3)",
"wv (m/s)",
"max. wv (m/s)",
"wd (deg)"]

All Time
(2009 – 2016)

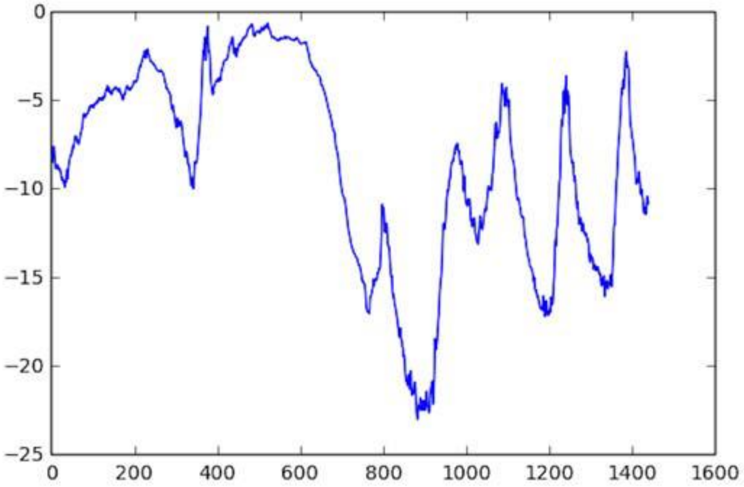
°C



10 mins

First 10 days

°C



10 mins

Download Jena Weather Dataset

- AWS
  - wget https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip

Normalize the Data

- Remember to normalize your data!

```
mean = float_data[:200000].mean(axis=0)
float_data -= mean
std = float_data[:200000].std(axis=0)
float_data /= std
```

Learning Parameters

- lookback = 720
  - Observations will go back 5 days.
- steps = 6
  - Observations will be sampled at one data point per hour.
- delay = 144
  - Targets will be 24 hours in the future.

Design a Data Generator

- data— The normalized data
- lookback—How many timesteps back the input data should go.
- delay—How many timesteps in the future the target should be.
- min_index and max_index—Indices in the data array that delimit which timesteps to draw from. This is useful for keeping a segment of the data for validation and another for testing.
- shuffle—Whether to shuffle the samples or draw them in chronological order.
- batch_size—The number of samples per batch.
- step—The period, in timesteps, at which you sample data. You'll set it to 6 in order to draw one data point every hour.

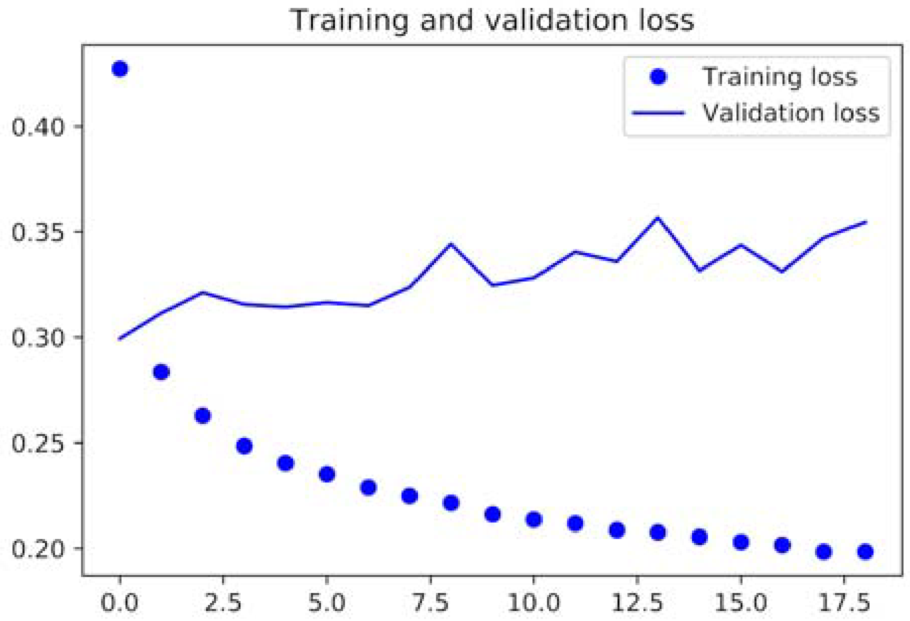
Timeseries Data Generator

```
def generator(data, lookback, delay, min_index, max_index, shuffle=False,
        batch_size=128, step=6):
    if max_index is None:
        max_index = len(data) - delay - 1
    i = min_index + lookback
    while 1:
        if shuffle:
            rows = np.random.randint(min_index + lookback, max_index, size=batch_size)
        else:
            if i + batch_size >= max_index:
                i = min_index + lookback
            rows = np.arange(i, min(i + batch_size, max_index))
            i += len(rows)
        samples = np.zeros((len(rows), lookback // step, data.shape[-1]))
        targets = np.zeros((len(rows),))
        for j, row in enumerate(rows):
            indices = range(rows[j] - lookback, rows[j], step)
            samples[j] = data[indices]
            targets[j] = data[rows[j] + delay][1]
        yield samples, targets
```

Create Baselines

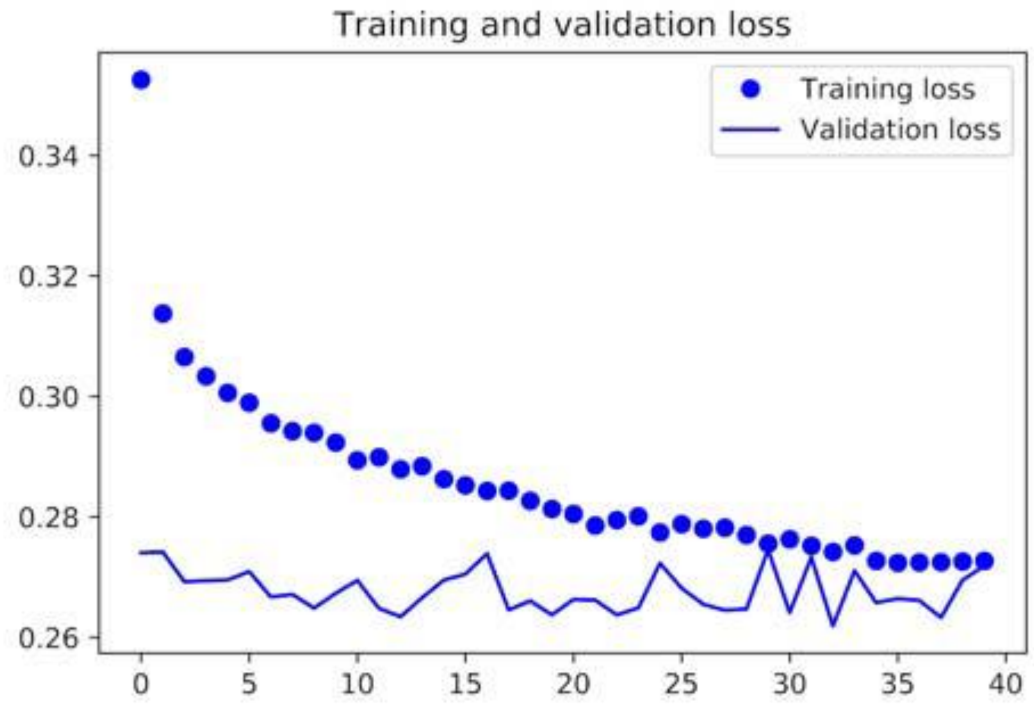
1. Common sense - Simply use last temperature as prediction
   – Mean absolute error 0.29 (2.57°C)
2. Using densely connected network

```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
model = Sequential()
model.add(layers.Flatten(input_shape=(lookback // step,
                  float_data.shape[-1])))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(1))
model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(train_gen,
steps_per_epoch=500, epochs=20, validation_data=val_gen,
validation_steps=val_steps)
```



Using Gated Recurrent Unit (GRU)

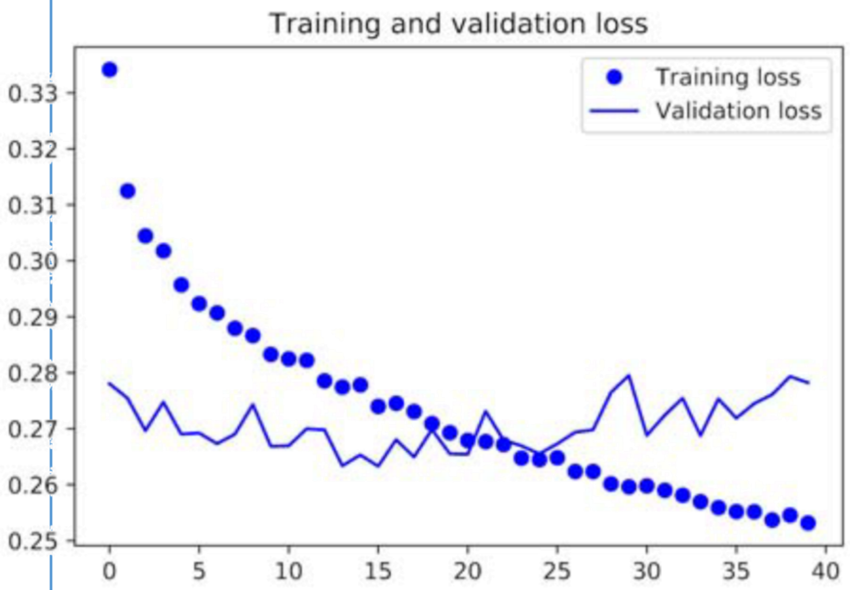
```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
model = Sequential()
model.add(layers.GRU(32, input_shape=(None, float_data.shape[-1])))
model.add(layers.Dense(1))
model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(train_gen,
                              steps_per_epoch=500,
                              epochs=20,
                              validation_data=val_gen,
                              validation_steps=val_steps)
```



Stacking Recurrent Layers

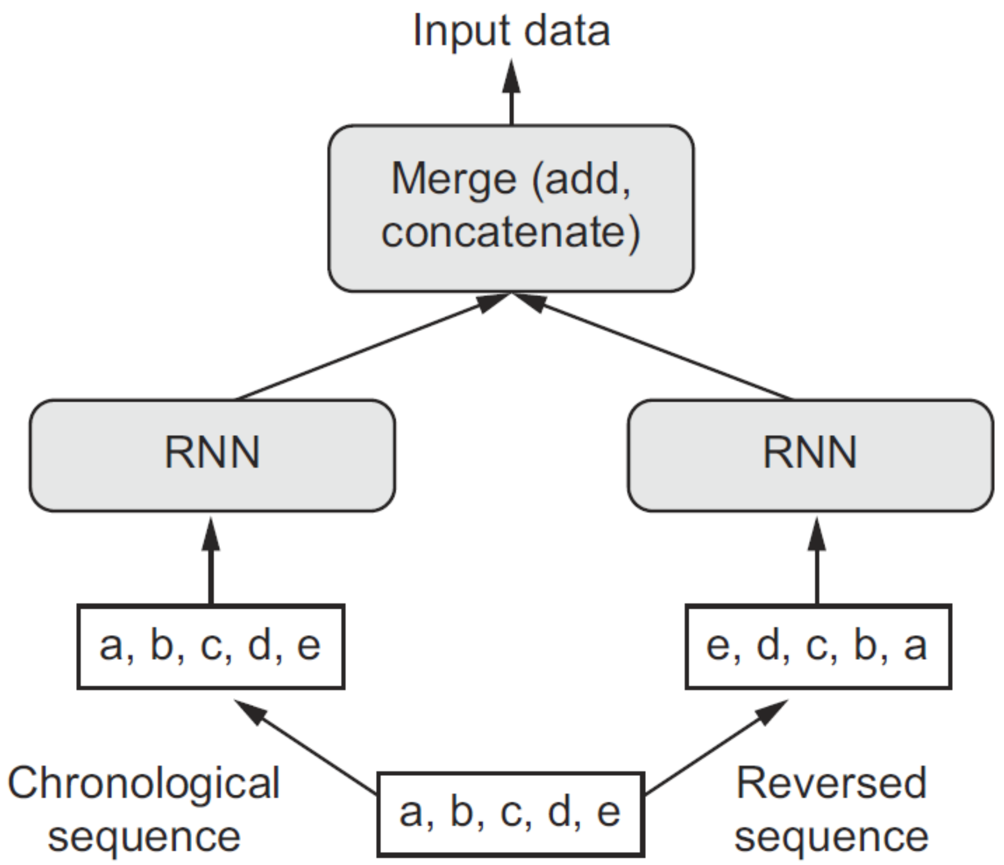
- To stack recurrent layers, all intermediate layers should return their full sequence of outputs (a 3D tensor) (return_sequences=True.)

```
model = Sequential()
model.add(layers.GRU(32,
        dropout=0.1,
        recurrent_dropout=0.5,
        return_sequences=True,
        input_shape=(None, float_data.shape[-1])))
model.add(layers.GRU(64, activation='relu',
        dropout=0.1,
        recurrent_dropout=0.5))
        model.add(layers.Dense(1))
        model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(train_gen,
        steps_per_epoch=500,
        epochs=40,
        validation_data=val_gen,
        validation_steps=val_steps)
```



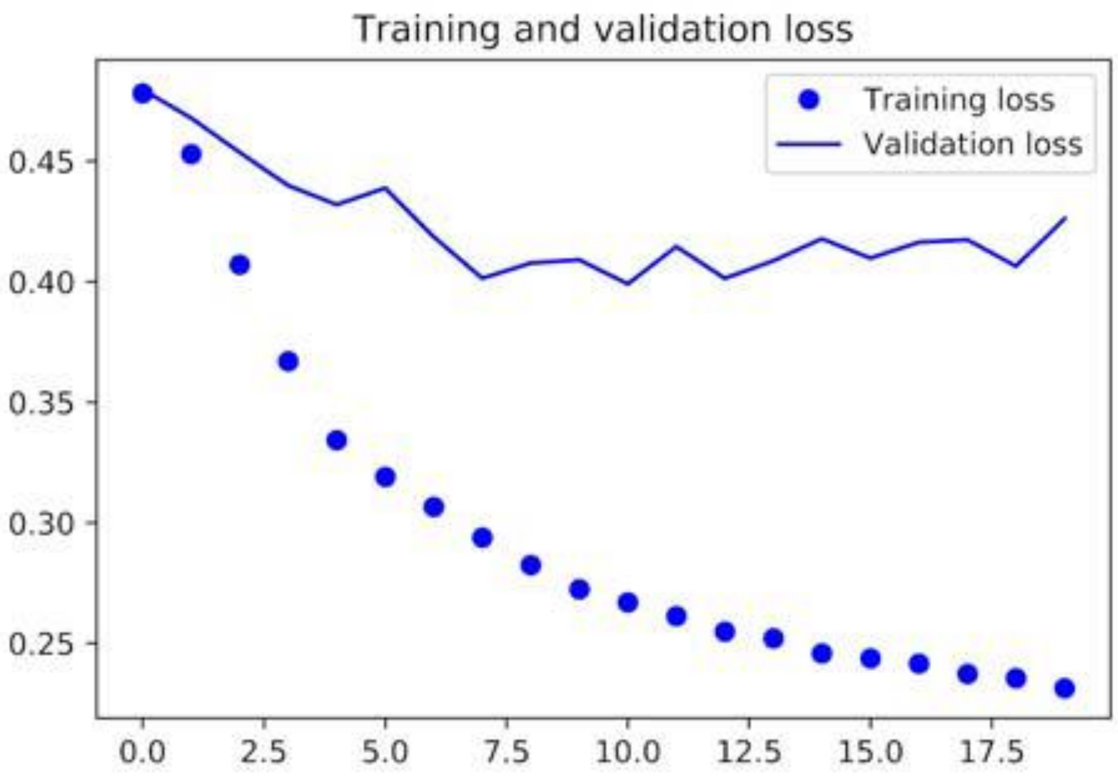
Bidirectional RNN

- A bidirectional RNN exploits the order sensitivity of RNNs
- Commonly used for Natural Language Processing (NLP)



Using Reversed Data for Training

- Perform even worse than the common-sense baseline



Bi-directional GRU for Temperature Prediction

- Get similar performance with regular GRU

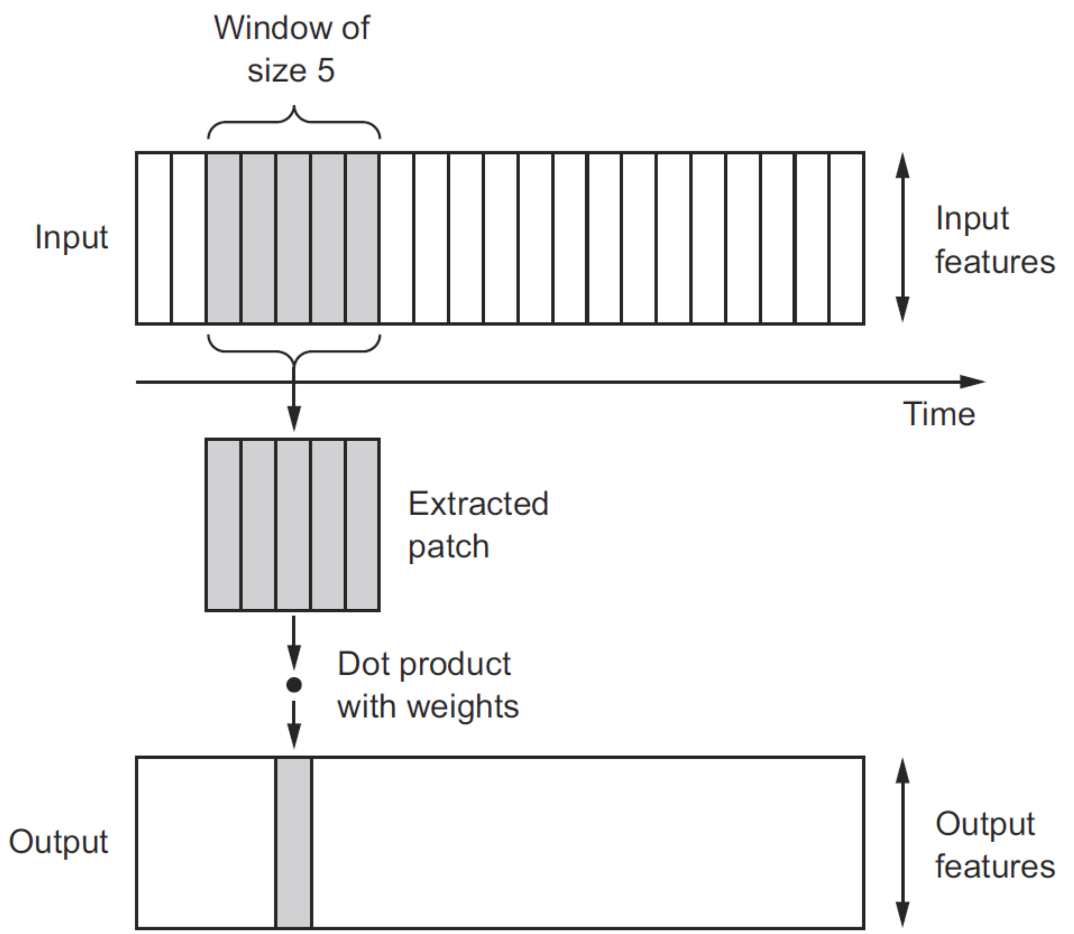
```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
model = Sequential()
model.add(layers.Bidirectional(
layers.GRU(32), input_shape=(None, float_data.shape[-1])))
model.add(layers.Dense(1))
model.compile(optimizer=RMSprop(), loss='mae')
history = model.fit_generator(train_gen,
                              steps_per_epoch=500,
                              epochs=40,
                              validation_data=val_gen,
                              validation_steps=val_steps)
```

Going Further

- Adjust the number of units in each recurrent layer in the stacked setup
- Adjust the learning rate used by the RMSprop optimizer
- Try LSTM layers
- Try using a bigger densely connected regressor on top of the recurrent layers
- Don't forget to eventually run the best-performing models (in terms of validation) on the test set!

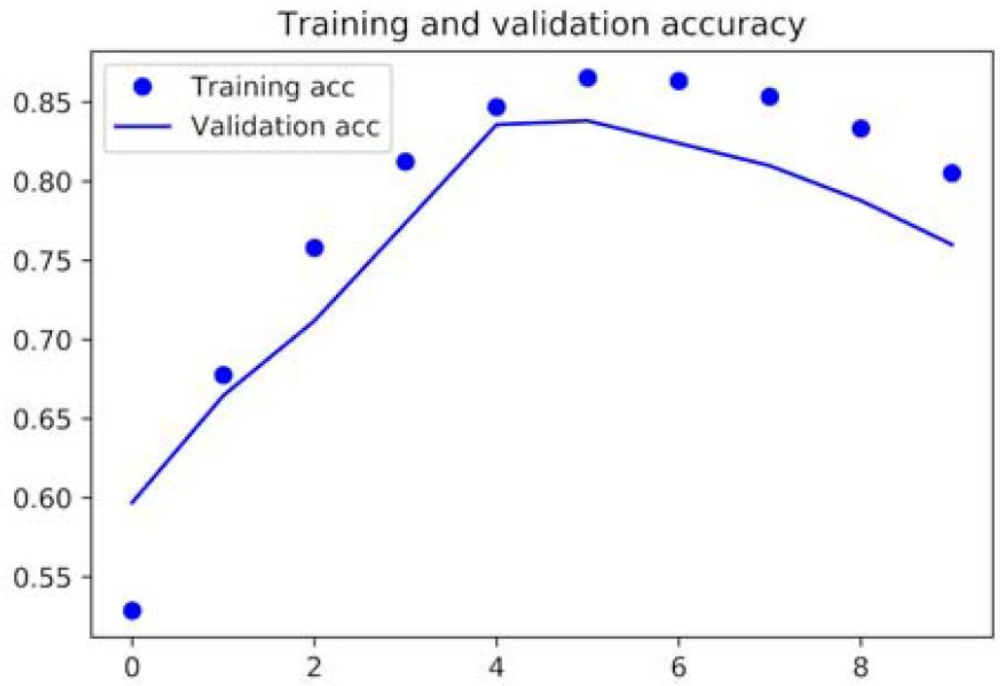
Sequence Processing with ConvNets

- 1-D convolution for sequence data



Building a 1D ConvNet Model for IMDB Dataset

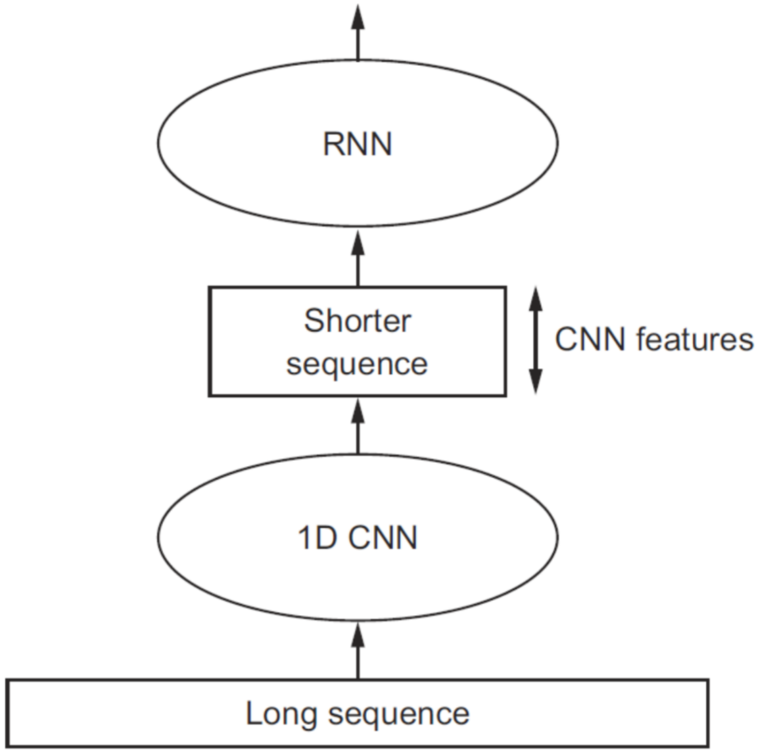
```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
model = Sequential()
model.add(layers.Embedding(max_features, 128,
input_length=max_len))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1, activation='sigmoid'))
model.summary()
model.compile(optimizer=RMSprop(lr=1e-4),
            loss='binary_crossentropy',
            metrics=['acc'])
history = model.fit(x_train, y_train,
            epochs=10,
            batch_size=128,
            validation_split=0.2)
```



Combining CNN & RNN for Long Sequences

- Prepare a high-resolution data and use 1D CNN to shorten the sequence

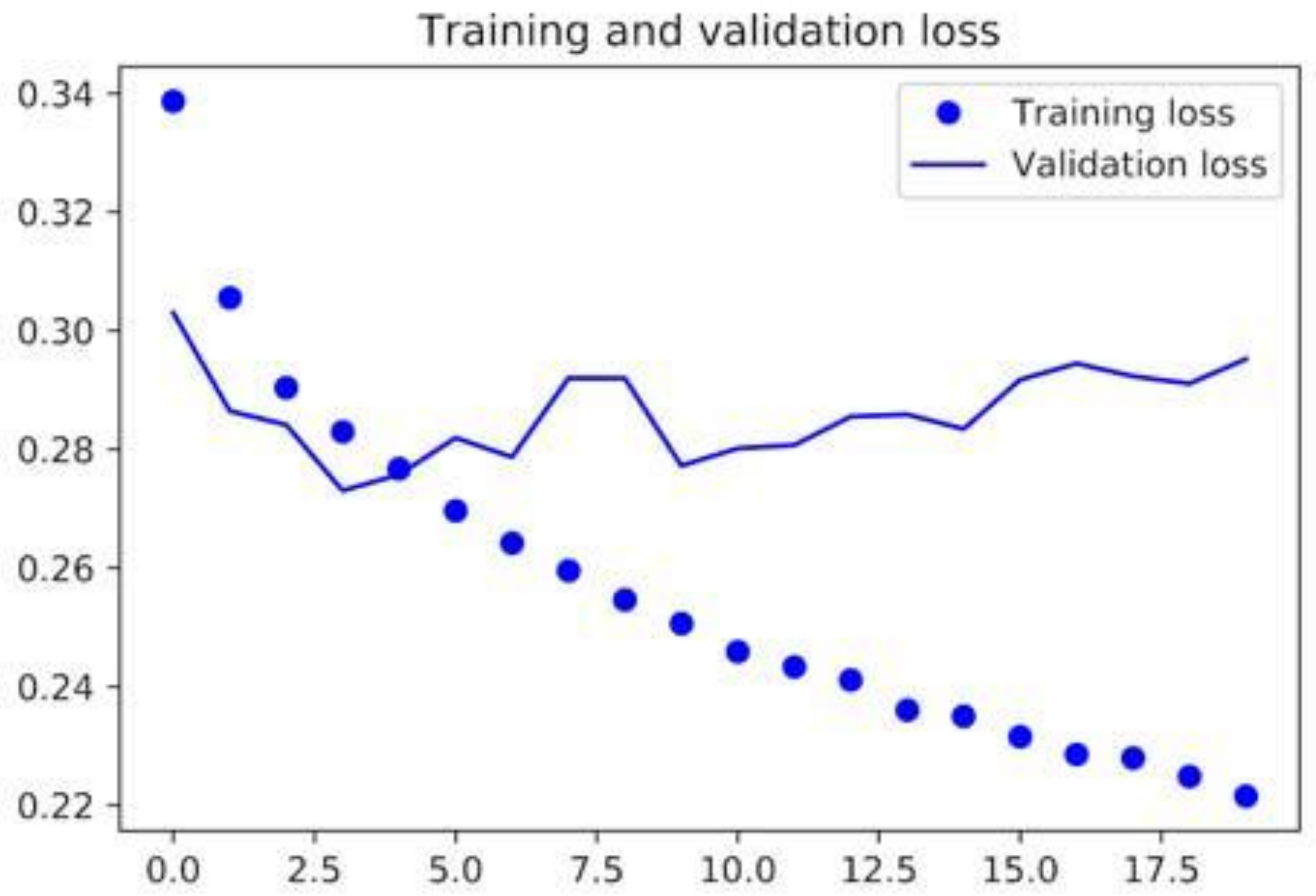
```
from keras.models import Sequential
from keras import layers
from keras.optimizers import RMSprop
model = Sequential()
model.add(layers.Conv1D(32, 5, activation='relu',
input_shape=(None, float_data.shape[-1])))
model.add(layers.MaxPooling1D(3))
model.add(layers.Conv1D(32, 5, activation='relu'))
model.add(layers.GRU(32, dropout=0.1,
recurrent_dropout=0.5))
model.add(layers.Dense(1))
model.summary()
model.compile(optimizer=RMSprop(), loss='mae')
```



Higher-resolution data generators for Jena Data

```
step = 3
lookback = 720
delay = 144
train_gen = generator(float_data, lookback=lookback,
                      delay=delay, min_index=0,
                      max_index=200000, shuffle=True,
                      step=step)
val_gen = generator(float_data, lookback=lookback,
                      delay=delay, min_index=200001,
                      max_index=300000, step=step)
test_gen = generator(float_data, lookback=lookback,
                      delay=delay, min_index=300001,
                      max_index=None, step=step)
val_steps = (300000 - 200001 - lookback) // 128
test_steps = (len(float_data) - 300001 - lookback) // 129
```

Results of 1D ConvNet + RNN on Jena Dataset



An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling

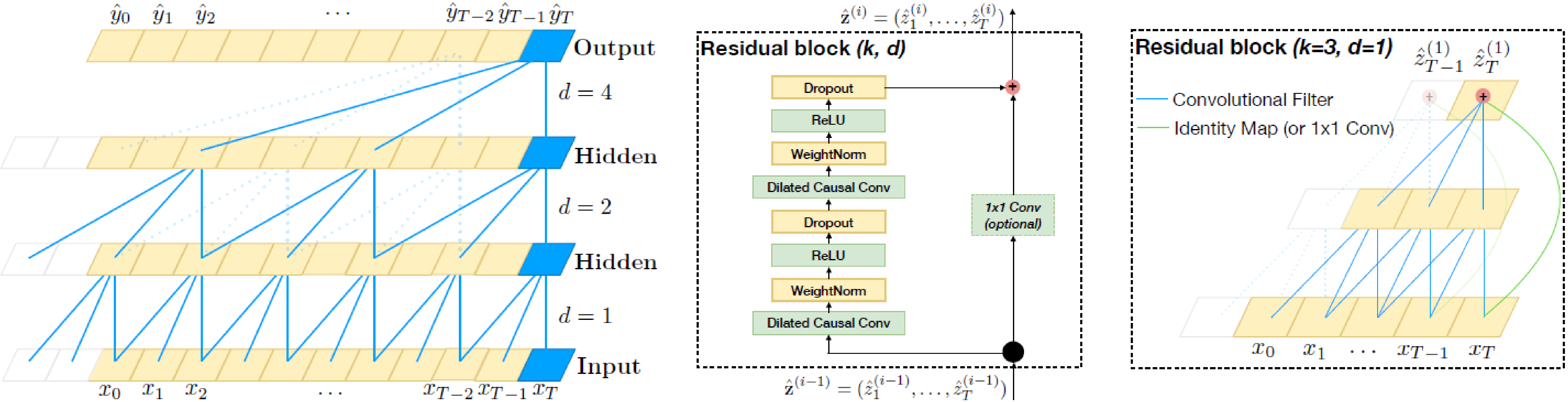
- Shaojie Bai, J. Zico Kolter, Vladlen Koltun (CMU & Intel Labs), April, 2018

- The models are evaluated on many RNN benchmarks
- A simple temporal CNN model outperforms RNN / LSTMs across a diverse range of tasks and datasets!


We knew CNN is better than RNN/LSTM for a while.

Temporal Convolutional Network (TCN)

- Dilated causal convolution



Experimental Results

Sequence Modeling Task	Model Size ($\approx$)	Models			
		LSTM	GRU	RNN	TCN
Seq. MNIST (accuracy^h)	70K	87.2	96.2	21.5	**99.0**
Permuted MNIST (accuracy)	70K	85.7	87.3	25.3	**97.2**
Adding problem T=600 (loss$^\ell$)	70K	0.164	**5.3e-5**	0.177	**5.8e-5**
Copy memory T=1000 (loss)	16K	0.0204	0.0197	0.0202	**3.5e-5**
Music JSB Chorales (loss)	300K	8.45	8.43	8.91	**8.10**
Music Nottingham (loss)	1M	3.29	3.46	4.05	**3.07**
Word-level PTB (perplexity$^\ell$)	13M	**78.93**	92.48	114.50	88.68
Word-level Wiki-103 (perplexity)	-	48.4	-	-	**45.19**
Word-level LAMBADA (perplexity)	-	4186	-	14725	**1279**
Char-level PTB (bpc$^\ell$)	3M	1.36	1.37	1.48	**1.31**
Char-level text8 (bpc)	5M	1.50	1.53	1.69	**1.45**

The Fall of RNN/LSTM

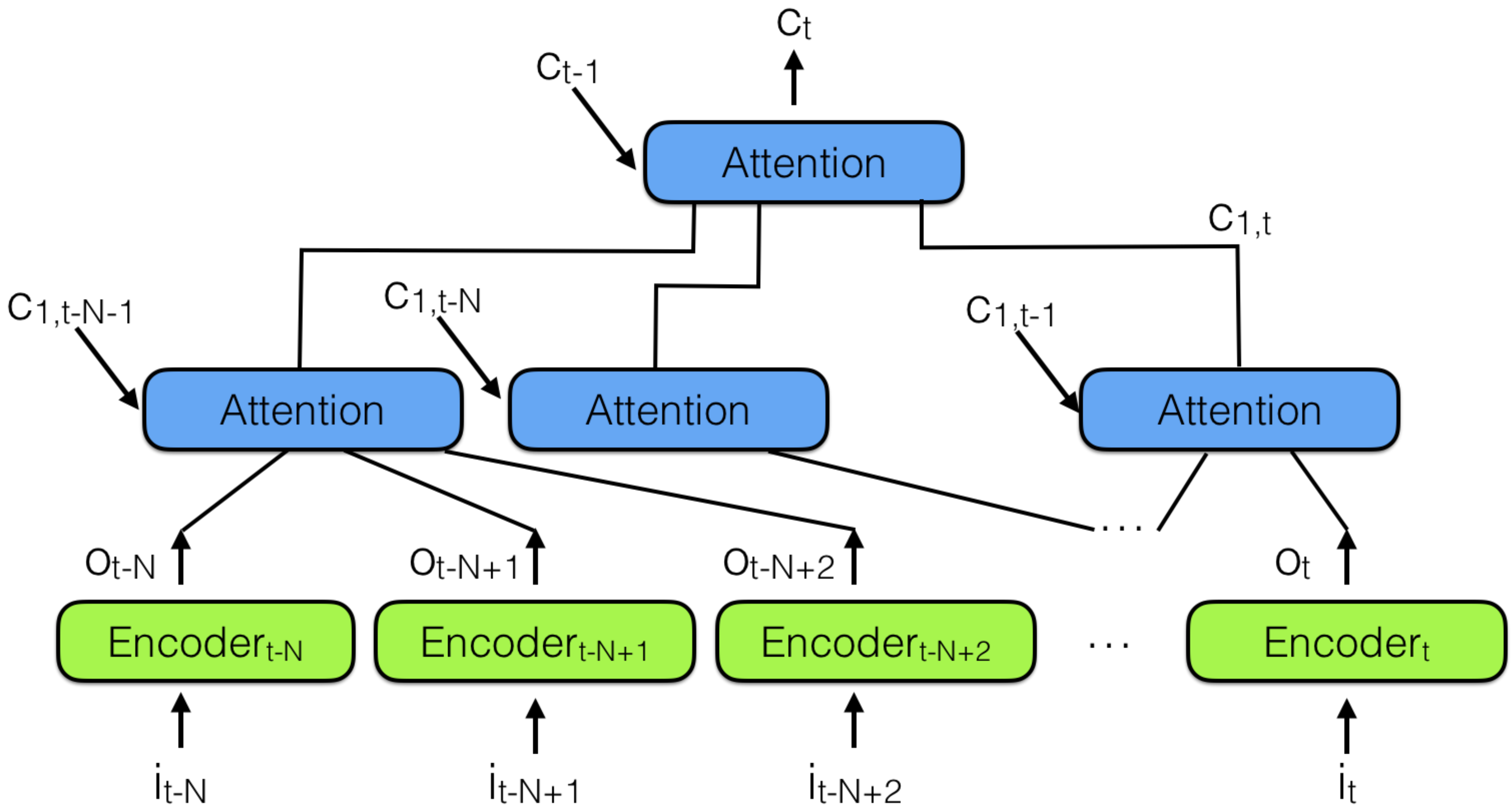
Eugenio Culurciello

Professor of Biomedical Engineering, Purdue University

April 13, 2018

https://towardsdatascience.com/the-fall-of-rnn-lstm-2d1594c74ce0

Hierarchical Neural Attention Encoder




I got a dig bick
You that read wrong
You read that wrong too

Attention is All You Need!

A. Waswani et al., *NIPS*, 2017

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