1) 1) 1)

1)(

. (21676295). 2018 ,"
"(2462018QZDX02) . 1966
.E-mail: liujw@cup.edu.cn. 1995 .E-mail: 714244712 @qq.com.
1963 E-mail: luoxl@cup.edu.cn.

network structure and training algorithm. Afterwords, we introduce the extended model of the memory network and its application in different fields and scenarios. Finally, the future research direction of the memory network is prospected.

Key words recurrent neural network; long short term memory network; memory network; neural turing machine; natural language processing

1

20 80 Recurrent Neural Network, RNN RNN

RNN

RNN

Hochreiter S Schmidhuber J 1997 Long Short-Term Memory LSTM [1] RNN

20 80 LSTM RNN

LSTM RNN

2014 Weston J, Chopra S, Bordes A Memory Network MN [2]

Google DeepMind Neural Turing Machine NTM [3]

Sukhbaatar S, Weston J, Fergus R

[4]

2017 Google Transformer [5] RNN

2

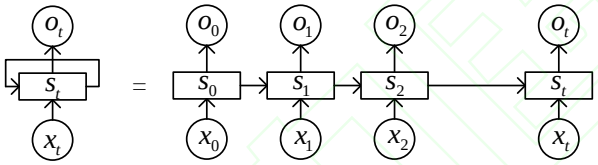
2014

[1] [3]

[2] [5][4]

2.1

1 RNN



1 RNN

RNN

RNN U,V,W

RNN

RNN

RNN

2.2

LSTM RNN

RNN

f Ux_t Ws_{t-1} tanh ReLU

s_{-1}

$o_t = soft\max(Vs_t)$ 2

o_t t

o_t t

V V

o_t t

s_t s_t

t

t s_t

s_t

x_t t x_1

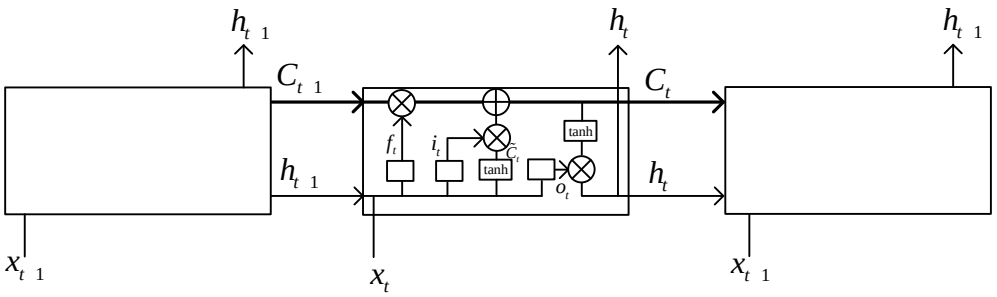
s_t t

s_t

$s_t = f(Ux_t + Ws_{t-1})$ 1

LSTM RNN LSTM

2



2 LSTM

LSTM 2 tanh

$\tilde{C}_t$

,

LSTM

i_t $(W_{t-1}\ [h_{t-1}, x_t]\ \ b_i)$ 4

$\tilde{C}_t$ $\tanh(W_c\ [h_{t-1}, x_t]\ \ b_c)$ 5

sigmoid

Sigmoid 0 1

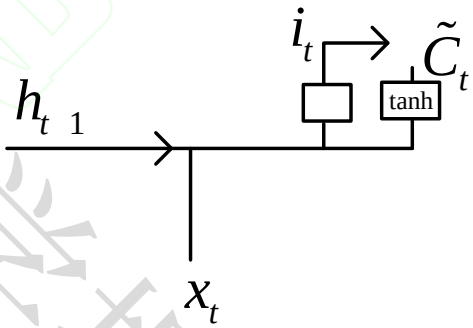
0

1 LSTM

LSTM

sigmoid

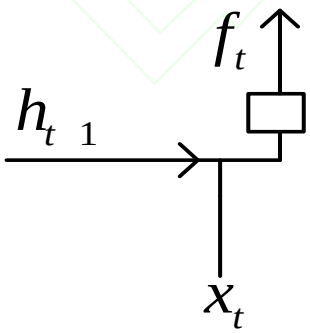
3 h_{t-1} x_t f_t



4 LSTM

f_t $(W_{t-1}\ [h_{t-1}, x_t])\ \ b_f$ 3

C_{t-1} 0 1



3 LSTM

C_t 5 C_{t-1}

i_t f_t C_{t-1} f_t

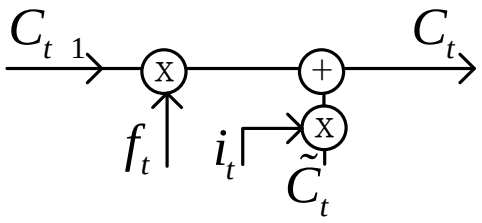
i_t $\tilde{C}_t$

f_t C_{t-1} i_t $\tilde{C}_t$

C_t

4 sigmoid

C_t f_t C_{t-1} i_t $\tilde{C}_t$ 6



5 LSTM

h_t o_t $\tanh(c_t)$ 11

Greff K [6] LSTM

LSTM

LSTM

2.3

C_t 6 sigmoid 2014 Google DeepMind [3]

o_t C_t

1936 ——

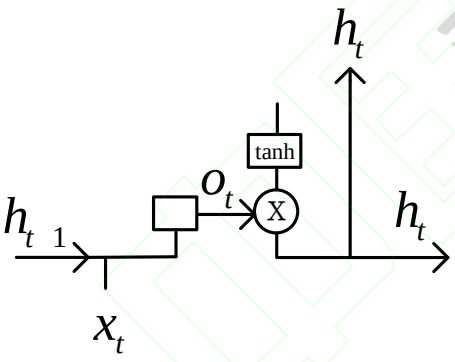
tanh C_t -1 1

NTM 7

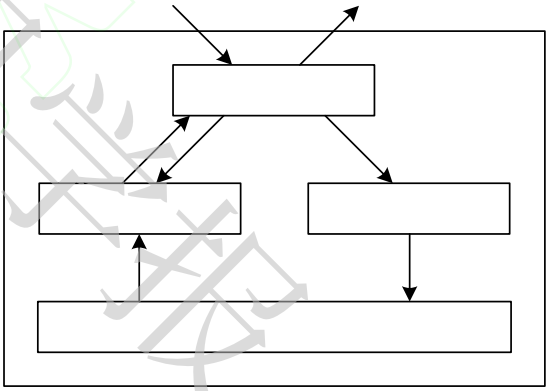
o_t h_t

o_t $(W_o [h_{t-1}, x_t] b_o)$ 7

h_t o_t $\tanh(C_t)$ 8



6 LSTM



7

NTM

LSTM c_t NTM

h_t t **1**

M_t Î ¡ $^{N' M}$ t

N M

w_t Î ¡ ^{N} t read head

N w_t

i_t

f_t W h_{t-1}, x_t 9

o_t

$\hat{c}_t$ tanh

c_t f_t c_{t-1} i_t $\hat{c}_t$ 10

$\sum_i w_t(i) = 1, 0 \quad w_t(i) \quad 1 \quad w_t \quad N \quad i \quad t$

M

$w_t(i)$

N

M r_t $M_t(i)$

3

$M_t(i)$

w_t NTM

$r_t \neg \sum_i w_t(i) M_t(i)$ 12

8

r_t w_t

2

$M_t(i)$ k_t

LSTM

t k_t

write head t w_t

M_t $M_t(i)$

e_t w_t e_t

w_t^c

M (0,1)

$w_t^c(i) \neg \frac{\exp\left(b_t K[k_t, M_t(i)]\right)}{\sum_j \exp\left(b_t K[k_t, M_t(j)]\right)}$ 15

M_{t-1}

K

$\%M_t(i) ? M_{t-1}(i)[1 \quad w_t(i)e_t]$ 13

$K[u,v] = \frac{u \times v}{\|u\| \times \|v\|}$ 16

1 1 $M_{t-1}(i)$

b_t

$[1- w_t(i)e_t]$

i k_t

$w_t(i)$ e_t 1

M_t $M_t(i)$

0 $w_t(i)$

e_t 0

M a_t

0,1

$M_t(i) ? \%M_t(i) \quad w_t(i)a_t$ 14

g_t w_{t-1}

w_t^c

w_t^g sharpening

g_t

w_t^g ? $g_t w_t^c$ (1- g_t)w_{t-1} 17

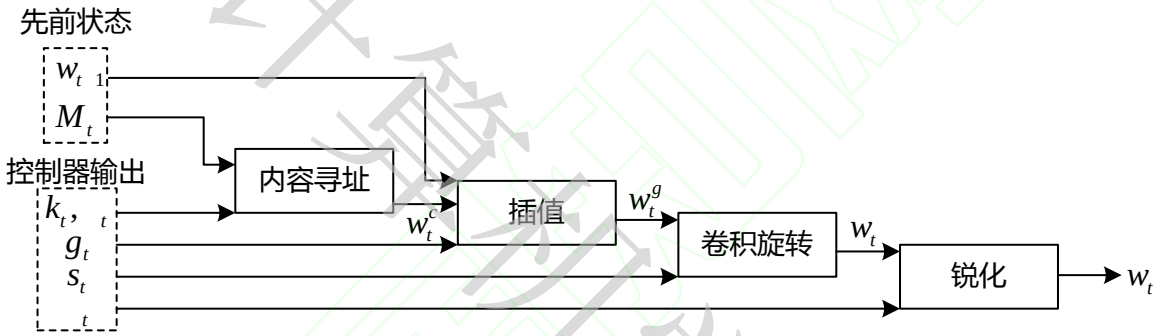
$w_t(i)$ ¬ $\frac{\%(i)^{g_t}}{\sum_j \%(i)^{g_t}}$ 19

N 0 N-1 s_t

w_t^g

$\%(i)$

$\%(i)$? $\sum_{j=0}^{N-1} w_t^g(j)s_t(i \quad j)$ 18



8 NTM

4

NTM LSTM

LSTM

2.4

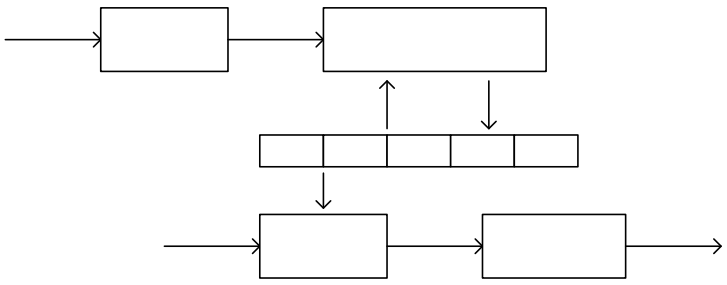
M_t

MN

Question Answers, QA

MN m I G

O R 9



9

1 x I

$I(x)$ $I(x)$ m

2 x

N k

k=1 N

o_1 $O_1(x,m)$ $\arg\max_{i\ 1,..,N} s_O(x,m_i)$ 20

s_O o_1

m_{o_1}

k=2 x m_{o_1}

o_2 $O_2(x,m)$ $\arg\max_{i\ 1,..,N} s_O([x,m_{o_1}],m_i)$

21

o_2 m_{o_2}

$x, m_{o_1}, m_{o_2}, \cdots, m_{o_k}$

3 m_{o_k} r

r

r $\arg\max_{w\ W} s_R([x,m_{o_1},m_{o_2}],w)$ 22

w W W s_R s_O

$s(x,y)$ $_x(x)^T U^T U$ $_y(y)$ 23

U n D D

n

x y

D

MN

margin ranking loss

$\max(0,\ s_O(x,m_{o_1})\ \ s_O(x,\bar{f}))$

$\bar{f}\ m_{o_1}$

$\max(0,\ s_O([x,m_{o_1}],m_{o_2})\ \ s_O([x,m_{o_1}],\bar{f}))$

$\bar{f}\ m_{o_2}$

$\max(0,\ s_R([x,m_{o_1},m_{o_2}],r)\ \ s_R([x,m_{o_1},m_{o_2}],\bar{r}))$

$\bar{r}\ r$

24

$\bar{f}, \bar{f}, \bar{r}$

0

MN Fader

QA [7] 14M

MN

QA WikiAnswers

Bordes [8]

MN

k=1

Fader 0

20 10

100

Bordes

20 200

13 6

1 MN

Bordes

MN

QA

1 MN QA

	F1
Fader [7]	0.54
Bordes [8]	0.73
MN	0.72
MN	0.82

QA :

1 5

RNN LSTM

RNN LSTM
[9]

MN
100 0.01 0.1
10 2

2 MN QA

q

k v

$\sqrt{d_k}$ d_k

softmax

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad 25$$

q k v

-

q k

v h

$$\text{MultiHead}(Q,K,V)=\text{Concat}(\text{head}_1,\text{K},\text{head}_h)W^O$$
$$\text{head}_i=\text{Attention}(QW_i^Q,KW_i^K,VW_i^V) \quad 26$$

W^O,W_i^Q,W_i^K,W_i^V

Position Embedding

RNN

$$PE_{(pos,2i)}=\sin(pos/10000^{2i/d_{model}})$$
$$PE_{(pos,2i+1)}=\cos(pos/10000^{2i/d_{model}}) \quad 27$$

pos i

d_{model}

$pos+k$ pos

$$\sin(pos+k)=\sin(pos)\cos(k)+\cos(pos)\sin(k)$$
$$\cos(pos+k)=\cos(pos)\cos(k)-\sin(pos)\sin(k) \quad 28$$

WMT 2014 - WMT 2014 -

Adam [10]

b_1=0.9 b_2=0.98 e=10^{-9}

$$l_{rate}=d_{\text{model}}^{-0.5}\cdot\min(step\_num^{-0.5},step\_num\times warmup\_steps^{-1.5}) \quad 29$$

warmup_steps

warmup_steps 4000

Dropout [11]

$P_{drop}=0.1$

[12] $e_{ls}=0.1$

5

ByteNet WMT 2014 -

1.2

Dilated Convolution

1

16

Deep-Att+PosUnk WMT 2014 -

256 LSTM

512

GNMT+RL WMT 2014 -

WMT 2014 -

8 8

1024 LSTM

1024 2
MoE MoE 2048
ConvS2S WMT 2014 - 200
WMT 2014 - BLEU
512 3
512
0.99
0.1 0.25
MoE WMT 2014 - WMT 4
2014 -
GNMT
LSTM 3

3

	BLEU			
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet[13]	23.75			
Deep-Att + PosUnk[14]		39.2		1.0 10^{20}
GNMT + RL[15]	24.6	39.92	2.3 10^{19}	1.4 10^{20}
ConvS2S[16]	25.16	40.46	9.6 10^{18}	1.5 10^{20}
MoE[17]	26.03	40.56	2.0 10^{19}	1.2 10^{20}
Deep-Att + PosUnk Ensemble[14]		40.4		8.0 10^{20}
GNMT + RL Ensemble[15]	26.30	41.16	1.8 10^{20}	1.1 10^{21}
ConvS2S Ensemble[16]	26.36	**41.29**	7.7 10^{19}	1.2 10^{21}
Transformer (base model)	27.3	38.1	**3.3 10^{18}**	
Transformer (big)	**28.4**	**41.0**	2.3 10^{19}	

4

DTN[18]	2017
WTN[19]	2017
AAN[20]	2018
BlendCNN[21]	2018 CNN
Action Transformer[22]	2018
Universal Transformers[23]	2018
Evolved Transformer[24]	2019
Set Transformer[25]	2019
Transformer-XL[26]	2019

2.6 5 RNN

-

RNN LSTM NTM

MN

5

-

1 RNN

MN

2 LSTM RNN

GPU MN

3 NTM RNN

4 MN NTM

NTM

MN

5

RNN	1986	
LSTM	1997	
NTM	2014	
MN	2014	
Transformer	2017	GPU

3

RNN

Attention-based Memory Selection Recurrent Network AMSRN [49]

RNN LSTM NTM MN

RNN AMSRN LSTM

LSTM MN LSTM

3.1 RNN

RNN

RNN RNN

RNN RNN

3.1.1 RNN

RNN

1 LSTM LSTM

$\{x_1, x_2, \cdots, x_t, \cdots\}$ x_t N 1-of-N

LSTM d

h_t R^d t LSTM

$M_t \quad [h_0, h_1, \cdots, h_{t\ 1}]$

2

h_t d w_{h1} w_{h2} LSTM

$M_t \quad [h_0, h_1, \cdots, h_{t\ 1}]$ h_t

d k_t

$$k_t \quad W_{kh} h_t \quad b_k \qquad 30$$

W_{kh} $\square^{d\ d}$ b_k $\square^{d}$

k_t LSTM

$M_t \quad [h_0, h_1, \cdots, h_{t\ 1}]$ h_i e_{ti}

$$e_{ti} \quad (h_i \circ w_{h1})\ k_t \qquad 31$$

$\circ$

$h_i \circ w_{h1}$ LSTM $M_t \quad [h_0, h_1, \cdots, h_{t\ 1}]$

h_t w_{h1}

$h_i \circ w_{h1}$ k_t

softmax e_{ti}

$_{ti}$

$$_{ti} \quad \frac{\exp(e_{ti})}{\sum_{i\ 0}^{t\ 1} \exp(e_{ti})} \qquad 32$$

w_{h2} h_i h_i

72 h_i r_t

r_t $_{ti}$ h_i

h_i $h_i \circ w_{h2}$ 33

$$r_t \quad \sum_{i\ 0}^{t\ 1} {}_{ti} h_i \qquad 34$$

r_t h_t

$$P_w \quad \text{softmax}(W_{ph} h_t \quad W_{pr} r_t \quad b_p) \qquad 35$$

W_{ph}, W_{pr}, b_p

LSTM+	134.09	93.74	102.04
LSTM+ +	133.36	92.49	86.85
RMN	123.32	64.41	121.28
RMR	134.30	71.04	145.24

7

LSTM

LSTM

Penn Treebank

Switchboard

Gigaword

RMN Recurrent

Memory Network RMR Recurrent Memory

Recurrent [30] AMSRN

RMN RMR

RMN RMR

AMSRN

3.1.2 RNN

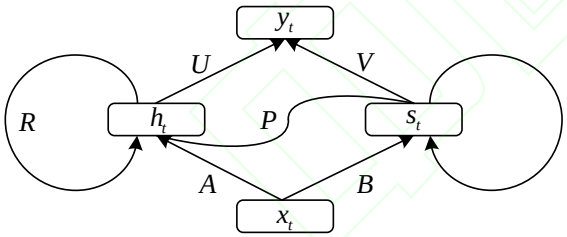
Mikolov T

[31]

RNN

LSTM

11



11 RNN

h_t

h_{t-1} x_t

$$h_t = (Ax_t + Rh_{t-1}) \quad (36)$$

RNN

s_t

$$s_t = (1-)Bx_t + s_{t-1}$$
$$h_t = (Ps_t + Ax_t + Rh_{t-1}) \quad (37)$$
$$y_t = f(Uh_t + Vs_t)$$

A R B P U V

0 1

0 1

Q t k

$s_k, k = t-1, \cdots, t-K$

Penn Treebank Corpus Text8

LSTM RNN

LSTM

3.1.3 RNN

[32]

1

L θ

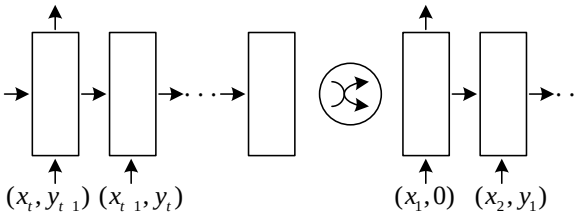
12

$L(D;)$ D x_i, y_i $_{i=1}^{t}$ $p(D)$

$$^* = \arg\min E_{D \sim p(D)}[L(D;)] \quad (38)$$

t

y_{t-1} x_t



12

2

LSTM

, Least Recently Used Access LRUA

LRUA RNN

RNN Wang J RNN [33]

w_t^u

w_{t-1}^u w_t^r w_t^w

w_t^u

[34] RNN

w_t^u w_{t-1}^u w_t^r w_t^w 39

w_t^r

k_t M_t

$$K(k_t, M_t(i)) \quad \frac{k_t \ M_t(i)}{\|k_t\| \|M_t(i)\|} \qquad 40$$

$$w_t^r(i) \quad \frac{\exp(K(k_t, M_t(i)))}{\sum_j \exp(K(k_t, M_t(i)))} \qquad 41$$

sigmoid w_{t-1}^r

w_{t-1}^{lu}

$$w_t^w \quad (\ ) w_{t-1}^r \quad (1 \quad (\ )) w_{t-1}^{lu} \qquad 42$$

w_{t-1}^{lu} $w_t^u(i)$

w_t^w 1 0

k_t

$$M_t(i) \quad M_{t-1}(i) \quad w_t^w(i) k_t \qquad 43$$

g $\|g\|$

$\|g\| > v$

$$g \neg \frac{gv}{\|g\|} \qquad 44$$

v g

3.2.1 LSTM

LSTM

LSTM

N_h LSTM

$O(N_h^2)$ LSTM

Danihelka I

Associative Long Short-Term Memory ALSTM [36] LSTM Holographic Reduced Representations HRR -

HRR -

$r \quad (a_r[1]e^{i\ r[1]}, a_r[2]e^{i\ r[2]}, \cdots)$

-

$\tilde{N}_{h^{(t)}} L$ $y \quad r \quad x \quad (a_r[1]a_x[1]e^{i(\ r[1] \quad x[1])}, a_r[2]a_x[2]e^{i(\ r[2] \quad x[2])}, \cdots)$

46

Pascanu R [35]

r_1, r_2, r_3

$$W = \sum_t \left(\frac{\left\| (\tilde{N}_{h^{(t)}} L) \frac{\P h^{(t)}}{\P h^{(t-1)}} \right\|}{\tilde{N}_{h^{(t)}} L} - 1 \right)^2 \qquad 45$$

RNN

3.2 LSTM

LSTM

LSTM

LSTM

LSTM LSTM

LSTM LSTM

$$h \quad \begin{matrix} h_{real} \\ h_{imaginary} \end{matrix} \qquad 48$$

$h \in \mathbb{R}^{N_h}, h_{real}, h_{imaginary} \in \mathbb{R}^{N_h/2}$

LSTM

$\hat{r}_i, \hat{r}_o$

$$\hat{g}_f, \hat{g}_i, \hat{g}_o, \hat{r}_i, \hat{r}_o \quad W_{xh}x_t \quad W_{hh}h_{t-1} \quad b_h \qquad 49$$

$$\hat{u} \quad W_{xu}x_t \quad W_{hu}h_{t-1} \quad b_u \qquad 50$$

0 1

$$\text{bound}(h) \quad \begin{matrix} h_{real} / d \\ h_{imaginary} / d \end{matrix} \qquad 51$$

d

$$\max(1, \sqrt{h_{real} \circ h_{real} \quad h_{imaginary} \circ h_{imaginary}})$$

$\in \mathbb{R}^{N_h/2}$ 52

/ ∘

d 1

u

r_i r_o

$$\begin{matrix} u \quad \text{bound}(\hat{u}) \\ r_i \quad \text{bound}(r_i) \\ r_o \quad \text{bound}(r_o) \end{matrix} \qquad 53$$

$r_i \in \mathbb{R}^{N_h}$

$r_o \in \mathbb{R}^{N_h}$

u g_i

$s \quad \{1, \ldots, N_{copies}\}$

-

$$r_{i,s} \quad \begin{matrix} P_s & 0 \\ 0 & P_s \end{matrix} \quad r_i \qquad 54$$

$$c_{s,t} \quad g_f \circ c_{s,t-1} \quad r_{i,s} \quad (g_i \circ u) \qquad 55$$

$r_{i,s}$ $P_s \in \mathbb{R}^{N_h/2 \; N_h/2}$

s

$$r \quad u \quad \begin{matrix} r_{real} \circ u_{real} & r_{imaginary} \circ u_{imaginary} \\ r_{real} \circ u_{imaginary} & r_{imaginary} \circ u_{real} \end{matrix} \qquad 56$$

$r_{o,s}$ $r_{i,s}$

$$r_{o,s} \quad \begin{matrix} P_s & 0 \\ 0 & P_s \end{matrix} \quad r_o \qquad 57$$

$$h_t \quad g_o \circ \text{bound}\left(\frac{1}{N_{copies}} \sum_{s=1}^{N_{copies}} r_{o,s} \quad c_{s,t}\right) \qquad 58$$

3.2.2 LSTM

Zhang X [37]

Tree Long Short-Term Memory Networks

TLSTM LSTM

TLSTM

$D(w)$

w

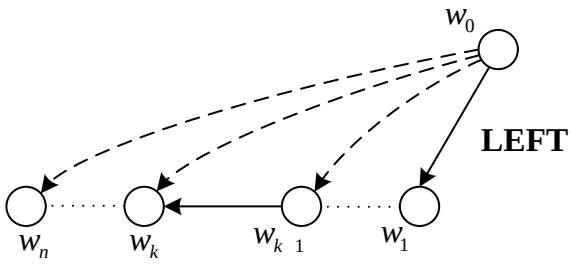
w_0 1, 2, , n

LEFT w_0

w_k w_0 w_{k-1} w_k

NX-LEFT 13

RIGHT NX-RIGHT



13

T

S

T

breadth-first search BFS

ROOT

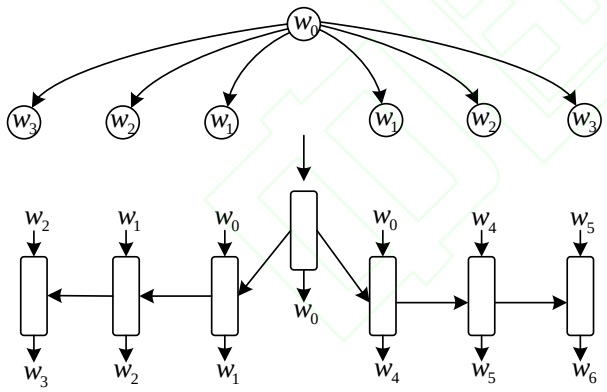
14

w

T S

$P(S|T)$ $P(w|D(w))$ 59

$w \in BFS(T) \backslash ROOT$



14 TLSTM

$D(w)$ <

> LSTM

LSTM LEFT LSTM

NX-LEFT RIGHT NX-RIGHT 15

LSTM

t $1,n$ $\langle w_t, z_t \rangle$ $D(w_t)$

t t w

z_t LEFT,RIGHT,NX-LEFT,NX-RIGHT

LSTM

W H

t $H[:,t]$

$D(w)$

x_t W_e $e(w_t)$

h_t $\text{LSTM}^{z_t}(x_t, H[:,t])$ 60

$H[:,t]$ h_t

y_t W_{ho} h_t

W_e $\square^{s \times |V|}$

W_{ho} $\square^{|V| \times d}$ V

s d

H $\square^{d \times (n-1)}$

$e(w_t)$ w_t LSTM^{z_t}

LSTM t x_t

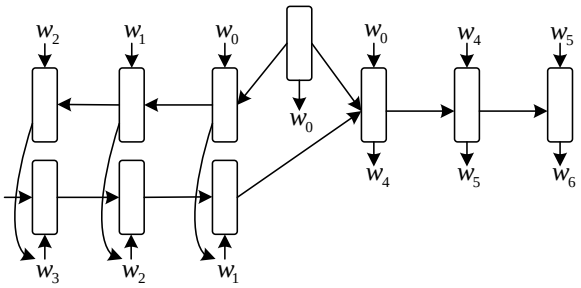
h_t h_t

LSTM

$D(w_t)$ softmax

$$P(w_t | D(w_t)) \quad \frac{\exp(y_t, w_t)}{\sum_{k=1}^{|V|} \exp(y_t, k)} \quad 61$$

TLSTM



15

w_0

p_j^t soft max$(u^T$ tanh$(W_{\ j}\ W_x x_t\ \ W_{\tilde{}}\ \tilde{}_{t\ 1}))$ $P(\hat{y}\,|\,\hat{x},S)$ $P(\hat{y}\,|\,\hat{x},S)$

72

1

$\tilde{}_t$ m p_j^t j 73 $\hat{x}$ $\hat{y}$ k $a(\hat{x},x_i)y_i$

$\tilde{}_t$ $j\ 1$ j $i\ 1$

r_t $P(\hat{y}\,|\,\hat{x},S)$

$c_S(\hat{x})$ x_i, y_i

r_t $(W_r\ [\tilde{}_t, x_t])$ 74 a $\hat{x}$

c_t x_i a

h_t c softmax

c_t r_t $\tilde{}_t$ f_t $\tilde{c}_t$ i_t $\hat{c}_t$ 75 $a(\hat{x},x_i)$ $e^{c(f(\hat{x}),g(x_i))}$ / $\ _{j\ 1}^{k}e^{c(f(\hat{x}),g(x_i))}$ 77

h_t o_t tanh(c_t) 76

Penn Treebank

RNN LSTM LSTM c

Stanford Sentiment Treebank

2

LSTM

$g(x_i,S)$

LSTM

T-CNN

3.2.4 LSTM LSTM $g(x_i,S)$ $\vec{h}_i$ $\overleftarrow{h}_i$ $g\ (x_i)$

LSTM S

$g\ (x_i)$ x_i

[40]

h_i, c_i LSTM$(g\ (x_i), h_{i\ 1}, c_{i\ 1})$ 78

h_i, c_i LSTM$(g\ (x_i), h_{i\ 1}, c_{i\ 1})$

k -

h_i c_i LSTM

S $\{(x_i,y_i)\}_{i\ 1}^{k}$ $c_S(\hat{x})$ $\overleftarrow{h}$ i $|S|$

3

$\hat{x}$ $\hat{x}$ $\hat{y}$ $\hat{x}$ $f(\hat{x},S)$

S $c_S(\hat{x})$ LSTM attLSTM(, ,)

$f(\hat{x}, S)$ attLSTM($f(\hat{x}), g(S), K$) 79

f g LSTM

K LSTM

$g(S)$ S x_i

k

$\hat{h}_k, c_k$ LSTM($f(\hat{x}), [h_{k-1}, r_{k-1}], c_{k-1}$)

h_k $\hat{h}_k$ $f(\hat{x})$

$$r_{k-1} = \sum_{i=1}^{|S|} a(h_{k-1}, g(x_i)) g(x_i) \quad (80)$$

$a(h_{k-1}, g(x_i))$ softmax($h_{k-1}^T g(x_i)$)

LSTM(x, h, c) x h

c a

$g(S)$ r_{k-1} h_{k-1}

LSTM attLSTM($f(\hat{x}), g(S), K$) h_K

3.3 MN

MN

MN

MN

MN

Dynamic Memory Networks DMN -

Key-Value Memory Networks KV-MemNN

Hierarchical Memory Network

HMN

Hierarchical Attentive Memory HAM

MN DMN

KV-MemNN

HMN

3.3.1

MN

[4]

$x_1, \cdots, x_n$ q a

x

x q

a

1 19

x_i

m_i c_i

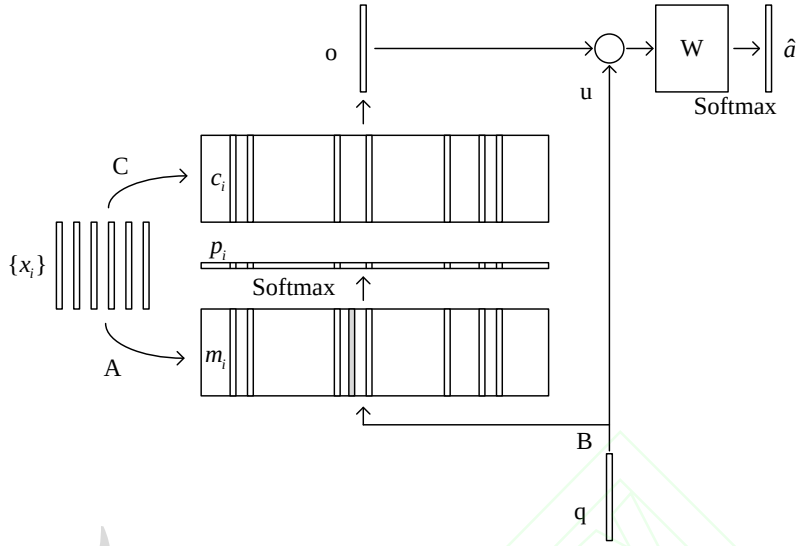
m_i u

p_i p_i

c_i o

o u W

$\hat{a}$



19

2

20

m_i $_j Ax_{ij}, c_i$ $_j Cx_{ij}$

u^{k-1} u $_j Bq_j$

Position Encoding PE

o^k u^k H

u^{k-1}

m_i $_j l_j Ax_{ij}$

u^{k-1} Hu^k o^k 81

$$l_{kj} = (1 - j/J) - (k/d)(1 - 2j/J) \quad 83$$

$\{x_i\}$ l_j l_{kj}

J d

W T_A T_C

$\hat{a}$ m_i c_i

$\hat{a}$ $\text{soft max}(Wu^{k-1})$ $\text{soft max}(W(o^k + u^k))$

82

$$m_i = \sum_j l_j Ax_{ij} + T_A(i) \quad 84$$

$$c_i = \sum_j Cx_{ij} + T_C(i) \quad 85$$

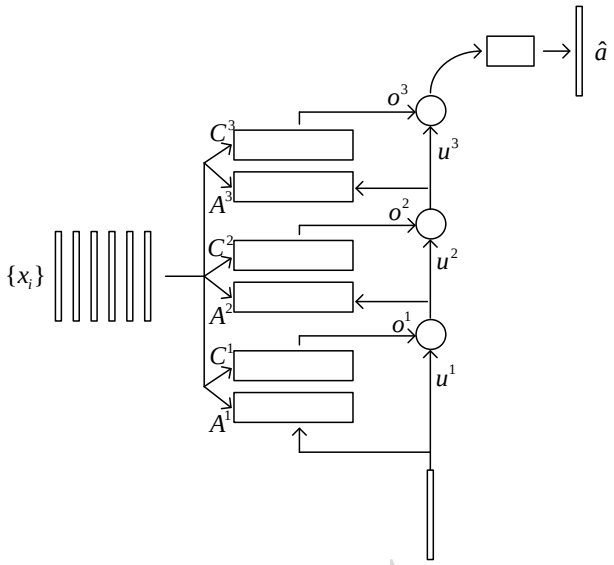
Bag of Words BoW

x_{ij} i j

i , $\hat{a}$

a

x_i $\{x_{i1}, x_{i2}, \ldots, x_{in}\}$



20

Penn Treebank Text8

RNN LSTM Structurally Constrained Recurrent Nets, SCRN

3.3.2

[41]

$u^{k\ 1}$ u^k o^k

$u^{k\ 1}$

$$T^k(u^k) \quad (W_T^k u^k \quad b_T^k) \qquad 86$$

$$u^{k\ 1} \quad o^k \ T^k(u^k) \quad u^k \ (1 \quad T^k(u^k)) \qquad 87$$

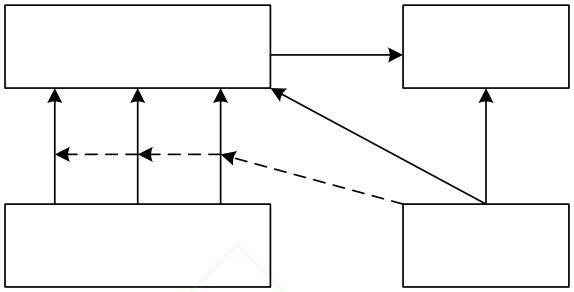
W_T^k, b^k k

T^k k

3.3.3

QA Kumar [42]

21



21 DMN

1

T_I

$w_1, \ldots, w_{T_I}$ Gated Recurrent Unit GRU

t x_t h_t GRU

$$z_t \quad (W^{(z)}x_t \quad U^{(z)}h_{t\ 1} \quad b^{(z)})$$
$$r_t \quad (W^{(r)}x_t \quad U^{(r)}h_{t\ 1} \quad b^{(r)})$$
$$\tilde{h}_t \quad \tanh(Wx_t \quad r_t \circ Uh_{t\ 1} \quad b^{(h)}) \qquad 88$$
$$h_t \quad z_t \circ h_{t\ 1} \quad (1 \quad z_t) \circ \tilde{h}_t$$

$\circ$

$W^{(z)}, W^{(r)}, W$ $\square^{n_H \ n_I}$ $U^{(z)}, U^{(r)}, U$ $\square^{n_H \ n_H}$

n GRU

$h_t \quad GRU(x_t, h_{t\ 1})$

RNN

GRU

T_C T_I c_t

t

T_C

2

T_Q

t

q_t $GRU(L[w_t^Q], q_{t-1})$ L w_t^Q

t

q q_{T_Q}

3

c

q m^{i-1}

g_t^i $G(c_t, m^{i-1}, q)$ c_t

g_t^i c m

q

$z(c,m,q)$ $[c, m, q, c \circ q, c \circ m, |c - q|, |c - m|,$

$c^T W^{(b)} q, c^T W^{(b)} m]$ 89

$z(c,m,q)$

$G(c,m,q)$

$G(c,m,q)$ $(W^{(2)} \tanh(W^{(1)} z(c,m,q) + b^{(1)}) + b$

90

GRU $c_1, \cdots, c_{T_C}$

GRU g_t^i

GRU t

h_t^i $g_t^i GRU(c_t, h_{t-1}^i) + (1 - g_t^i) h_{t-1}^i$

e^i $h_{T_C}^i$

e^i

m^i $GRU(e^i, m^{i-1})$ T_M

m^{T_M}

4

GRU

a_0 m^{T_M} y_t $\text{softmax}(W^{(a)} a_t)$

a_t a_t $GRU([y_{t-1}, q], a_{t-1})$

GRU

y_t

Facebook bAbI

20 93.6%

93.3%

Stanford Sentiment Treebank (SST)

97.5%

3.3.4 -

QA Miller [43]

KV-MemNN 22

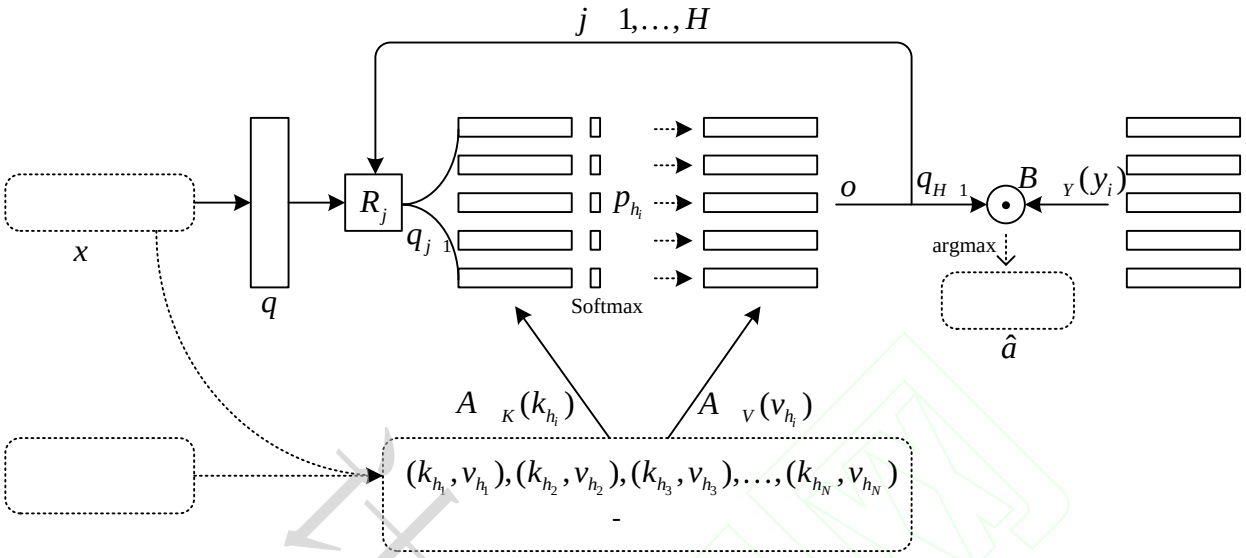
- Key-value

key

value

KV-MemNN x

$(k_1, v_1), \ldots, (k_M, v_M)$



22 KV-MemNN

1 Key Hashing j hop R_j

N

$(k_{h_1}, v_{h_1}), \ldots, (k_{h_N}, v_{h_N})$ 1000 q

p_{h_i} s o f t m a $q_{j\ 1}^T$ x A $_K$ k_{h_i}

2 Key Addressing H

Softmax k_{h_i} x $\hat{a}$ $\text{argmax}_{i\ 1,\ldots,C}\text{softmax}(q_{H\ 1}^T B\ _Y(y_i))$

91

p_{h_i} $\text{Softmax}(A\ _X(x)\ A\ _K(k_{h_i}))$ 93 y_i Y

D A

$d' D$

3 Value Reading 3.3.5

o $p_{h_i} A\ _V(v_{h_i})$ Chandar

Maximum Inner Product Search

x MIPS

q $A\ _X(x)$ Hierarchical Memory Network HMN [44]

o q

q_2 $R_1(q\ \ o)$ R_1 d d

MN HMN

1 HMN

hash

MIPS

MIPS

MIPS

2 HMN

MIPS

HMN

MIPS MIPS

HMN K-MIPS

$\{x_1,\ldots,x_n\}$ q K-MIPS

$\text{argmax}_i^{(K)} q^T x_i$ $\text{argmax}^{(K)}$ K

$q^T x_i$ $\{x_1,\ldots,x_n\}$

q

HMN K-MIPS

MIPS

softmax

$$C \quad \text{argmax}^{(K)} h(q) M^T$$
$$R_{out} \quad \text{softmax}^{(K)}(h(q)M^T) \qquad 92$$
$$\text{softmax}(h(q)M[C]^T)$$

$h(q)$ $\square^d$ C K

MIP M $\square^{N\ d}$

N $M[C]$ M

$M[C]$ C

K-MIPS Auvolat [45]

K-MIPS MIPS

MIPS Maximum Cosine Similarity Search MCSS

$\text{argmax}_i^{(K)} \frac{q^T x_i}{\|q\|\|x_i\|}$ $\text{argmax}_i^{(K)} \frac{q^T x_i}{\|x_i\|}$ 93

x_i MCSS

MIPS

MIPS MCSS

P Q

MIPS MCSS

$P(x)$ $x, 1/2\ \|x\|_2^2, 1/2\ \|x\|_2^4, \ldots, 1/2\ \|x\|_2^{2^m}$

$Q(x)$ $x, 0, 0\ldots, 0$

94

q MIPS

$$\text{argmax}_i^{(K)} q^T x_i \square \text{argmax}_i^{(K)} \frac{Q(q)^T P(x_i)}{\|Q(q)\|_2 \ \|P(x_i)\|_2}$$

95

MIPS MCSS K [46]

K K

HMN

1 K mini-batch GPU

2

3 K

3.3.6 MN

(n)

n n

(n^2)

Andrychowicz

Hierarchical Attentive Memory

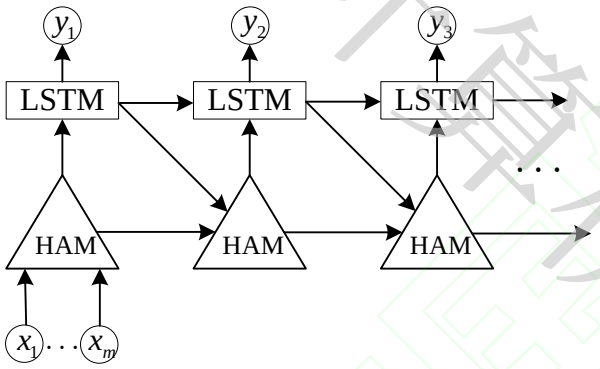
HAM [47]

$(\log n)$

(n)

HAM HAM

LSTM 23



23 HAM

x_1, x_2, L

y_1, y_2, L $x_i, y_i \hat{\mathrm{I}} \{0,1\}^b$ b

n n 2

HAM n

$|V| = 2n - 1$ $L \grave{\mathrm{I}} V$

$l(e)$ $r(e)$

e $e \hat{\mathrm{I}} V \setminus L$

HAM LSTM

HAM

1 EMBED(x_i)

x_i

0 JOIN

$h_e = \mathrm{JOIN}(h_{l(e)}, h_{r(e)})$

2

SEARCH p

1-p

a

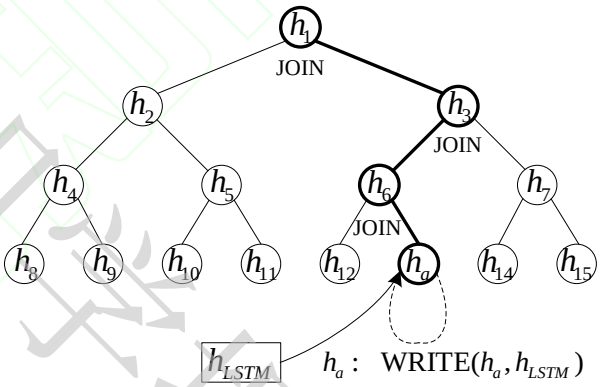
3 a h_a

LSTM $y_t \hat{\mathrm{I}} \{0,1\}^b$ sigmoid

y_t

4 24

a WRITE



24 HAM

EMBED ^{b} ® ^{d} JOIN

^{d} ^{d} ? ^{d} SEARCH

^{d} ^{l} [0,1] WRITE

^{d} ^{l} ? ^{d}

Multilayer Perceptrons MLPs

-

[48] x y

A

y

$$L \quad \log p(y \mid x, \ ) \quad \log \quad p(A \mid x, \ ) p(y \mid A, x, \ ) \quad 96$$

$$F \quad p(A \mid x, \ ) p(y \mid A, x, \ ) \quad L \quad 97$$

$$F \quad p(A \mid x, \ )[\quad \log p(y \mid A, x, \ ) \quad \log p(y \mid A, x, \ ) \quad \log p(A \mid x, \ )] \quad 98$$

LSTM HAM LSTM LSTM FIFO LSTM 99% 25% LSTM HAM 0.04% 2 4 LSTM LSTM HAM 2.48% $Q(\log n)$

3.3.7 MN

SimpleQuestions [50] QA QA

1 Freebase Reverb

s r o k $y \quad (s, r, \{o_1, \ldots, o_k\})$ $f(y)$ N_S N_S $f(y)$ 1 1/k

q $g(q)$ N_V N_V q 1 0

$y \quad (s, r, o)$ $h(y)$ $N_S \ N_V$ s o r

2

3

n n n n n

W_V $d \ N_V$ W_S $d \ N_S$ q y

$$S_{QA}(q, y) \quad \cos(W_V g(q), W_S f(y)) \quad 99$$

W_V W_S

y W_{VS} $d \ (N_V \ N_S)$

$$S_{RVB}(q, y) \quad \cos(W_V g(q), W_{VS} h(y)) \quad 100$$

W_V W_S

4

WebQuestions SimpleQuestions Reverb

WebQuestions 41.3 F1 41.2 SimpleQuestions 62-63 86 SimpleQuestions

Reverb 67%

3.3.8 DMN

DMN Xiong [51] DMN QA QA

1 QA

DMN GRU

GRU

GRU

Xiong GRU

$[w_1^j,\ldots,w_{M_i}^j]$

f_i

$f_i \quad {}_{M}^{j\ 1} l_j \circ w_j^i$ 101

$l_{jd} \quad (1 \quad j/M) \quad (d/D)(1 \quad 2j/M)$ 102

$l_j \quad l_{jd}$

d D M

f_i GRU

$\vec{f}_i \quad GRU_{fwd}(f_i, \vec{f}_{i\ 1})$

$\overleftarrow{f}_i \quad GRU_{bwd}(f_i, \overleftarrow{f}_{i\ 1})$ 103

$\overleftrightarrow{f}_i \quad \overleftarrow{f}_i \quad \vec{f}_i$

2 QA

QA VGG-19 CNN

q

F GRU $\overleftrightarrow{F}$

3

QA

$\overleftrightarrow{F} \quad \overleftrightarrow{f}_1,\cdots,\overleftrightarrow{f}_N$

$g_i^t \quad \overleftrightarrow{f}_i$

$\overleftrightarrow{f}_i$ q

g_i^t

$z_i^t \quad [\overleftrightarrow{f}_i \circ q; \overleftrightarrow{f}_i \circ m^{t\ 1}; |\ \overleftrightarrow{f}_i \quad q\ |; |\ \overleftrightarrow{f}_i \quad m^{t\ 1}\ |]$

$Z_i^t \quad W^{(2)} \tanh(W^{(1)} z_i^t \quad b^{(1)}) \quad b^{(2)}$

$g_i^t \quad \dfrac{\exp(Z_i^t)}{{}_{k\ 1}^{M_i} \exp(Z_i^t)}$

104

$\overleftrightarrow{f}_i$ i $m^{t\ 1}$

$\circ$

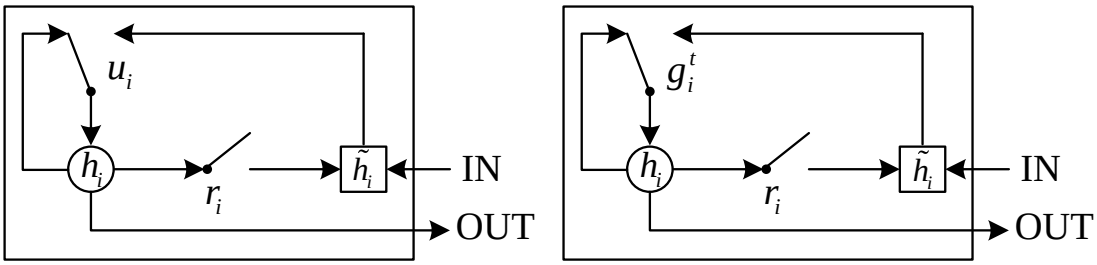
g_i^t

GRU GRU c_t

g_i^t c_t $\sum_{i=1}^{N} g_i^t \overleftrightarrow{h}_i$ GRU

GRU

$\overleftrightarrow{F}$



25 GRU GRU /

g_i^t GRU u_i

25 GRU

$$h_i = g_i^t \circ \tilde{h}_i + (1 - g_i^t) \circ h_{i-1} \quad 105$$

3.3.9 KV- Rama( )-249( )-238( )]TJEMC 12

h_N c_t

c_t m^{t-1}

m^t

$$m^t = GRU(c^t, m^{t-1}) \quad 106$$

GRU q

ReLU m^t

$$m^t = RuLU(W^t[m^{t-1}; c^t; q] + b) \quad 107$$

$W^t \in \mathbb{R}^{n_H \times n_H}, b \in \mathbb{R}^{n_H}, n_H$

Ramachandran DMN

Dynamic Memory

Tensor Network DMTN [52]

[53]

DMN 80%

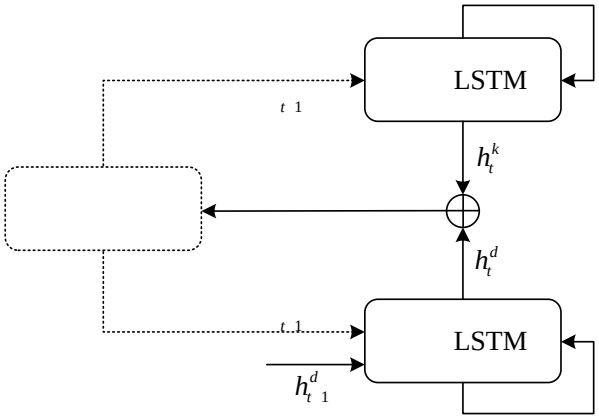
Facebook

bAbI 20%

Visual Question

Answering VQA VQA

$(k_1, v_1), \cdots, (k_T, v_T)$



Key CNN

I_i RNN

h_i^e

k_i h_i^e

26

Value I_i e_i^t $w_t \tanh(q \quad U_a k_i)$ 109

v_i (I_i) W_k, W_d, w_t, U_a

softmax

- (k_i, v_i)

26 $_i^t$ $\exp\{e_i^t\} / \sum_{j=1}^{N} \exp\{e_j^t\}$ 110

a_i -

LSTM $_{t-1}(K)$

h_t^k $f^k(\ _{t-1}(K), h_{t-1}^k)$ f^k $_t(K) \sum_{i=1}^{T} {}_i^{(t)} k_i$, $_t(V) \sum_{i=1}^{T} {}_i^{(t)} v_i$ 111

t q h_{t-1}^d $_i^t$

h_t^k $_t(K)$

$q \quad W_k h_t^k \quad W_d h_{t-1}^d$ 108 $_t(V)$

q i k_i

tanh i k_i **3** LSTM

LSTM

RNN h_t c_t

LSTM

x_t f_t

[55]

o_t

k

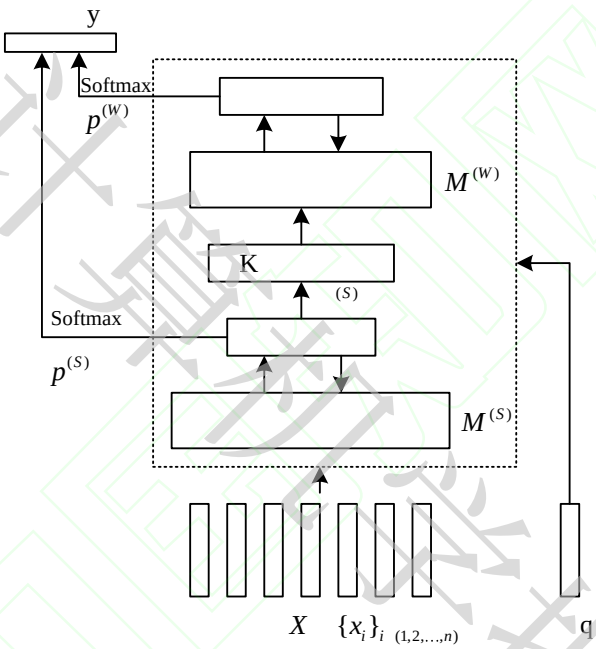
h_t softmax k

p_t

p_t $\text{soft}\max(U_p[h_t, x_t, {}_t(V)])$ b_p 112

3.3.10 HMN

27



27 HMN

n **K**

X $\{x_i\}_{i\ (1,2,\ldots,n)}$ q X (S) k

$M^{(S)}$

$M^{(W)}$

soft-search k GRU

$\bar{}$ $\{\bar{}_t\}_{t\ (1,2,\ldots,|t|)}$ t

y $\bar{}$ GRU GRU

$\vec{h}_t$ $G\vec{R}U(C^R\bar{}_t)$ $\bar{h}_t$ $G\bar{R}U(C^R\bar{}_t)$

C^R

GRU

$p^{(S)}$

$\vec{h}_t$ GRU $\overleftarrow{h}_t$

$M^{(W)}$ $\{m_t\}_{t\ (1,2,\ldots,|t|)}$ m_t $\vec{h}_t$ $\overleftarrow{h}_t$

m_t X t

$\overline{w}_t$

$\hat{}$ $\{\hat{}_t\}_{t\ (1,2,\ldots,|\hat{t}|)}$

$\hat{X}$

$u_R^{(S)}$ $\hat{w}$

$\{\hat{m}_t\}_{t\ (1,2.,\hat{t}\ ,}$

$^{(W)}$ $\{^{(W)}_t\}_{t\ (1,2,\ldots,|\hat{t}|)}$

$^{(W)}_t$ softmax(v^T tanh($Wu_R^{(S)}$ $U\hat{m}_t$)) 113

v $^{d\ 1}$,W $^{d\ d}$,U ? ? $^{d?\ d}$

Oriol Vinyals [53]

$\hat{w}$

$p^{(W)}(\ )$ $trans(p^{(W)}(\hat{}))$ $trans(\ ^{(W)})$ 114

$trans(\ )$

$p^{(W)}(\hat{w})$ Î ¡ $^{|\hat{t}|}$

$p^{(W)}(w)$ Î ¡ $^{|V|}$

0

$M^{(S)}$

$p^{(S)}$ $M^{(W)}$ $p^{(W)}$

$$p(w) = p^{(S)}(w) + p^{(W)}(w) \quad 115$$

y

HMN

HMN

3.4

3.4.1

urlanello

Active Long Term Memory Networks A-LTM [58]

Distillation Loss [59]

McClelland [60]

Hippocampus Neocortex

Catastrophic Inference CI

A-LTM

N

H

N

H N

A-LTM

N

N

N 0

N H H

H

$w_0^0 \quad w_0^* \quad w_1^0 \quad w_1^* \quad w_2^0 \sim N(0, \quad)$ 116

$f(w_0^*, w_1^*; x_1)$

N y_1

3.4.2

Colin Raffel [61] 28

Bahdanau [62]

h_t

a_{tj}

h_j c_t

$$c_t = \sum_{j=1}^{T} a_{tj} h_j \quad 117$$

T a_{tj} h_j

t

$$e_{tj} = a(s_{t-1}, h_j), a_{tj} = \frac{\exp(e_{tj})}{\sum_{k=1}^{T} \exp(e_{tk})} \quad 118$$

a

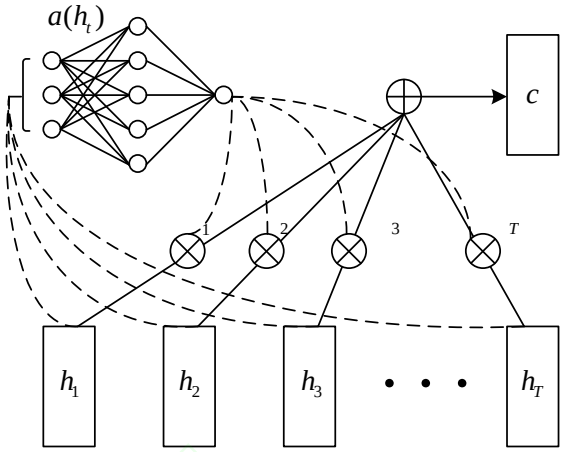
s_{t-1} h_j

s_t

s_t s_{t-1}

c_t t-1

$s_t = f(s_{t-1}, c_t, y_{t-1})$



28

h_t

$a(h_t)$ a a

h_t c_t

c_t

$$e_t = a(h_t), a_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_t)}, c = \sum_{t=1}^{T} a_t h_t \quad 119$$

a_t h_t

a_t h_t

c

T

T

h_t

$$c = \frac{1}{T} \sum_{t=1}^{T} h_t$$

x_t

$h_t = \mathrm{LReLU}(W_{xh}x_t + b_{xh})$ 120

W_{xh} $^{D' 2}$, b_{xh} ^{D} $\mathrm{LReLU}(x)$

$$\mathrm{LReLU}(x) = \max(x, 0.01x)$$

$$a(h_t) = \tanh(W_{hc}h_t + b_{hc})$$

104 c

s

$s = \mathrm{LReLU}(W_{cs}c + b_{cs}), W_{cs}$ $^{D' D}$, b_{cs} ^{D}

121

y

$y = \mathrm{LReLU}(W_{sy}s + b_{sy}), W_{sy}$ $^{1' D}$, b_{sy}

122

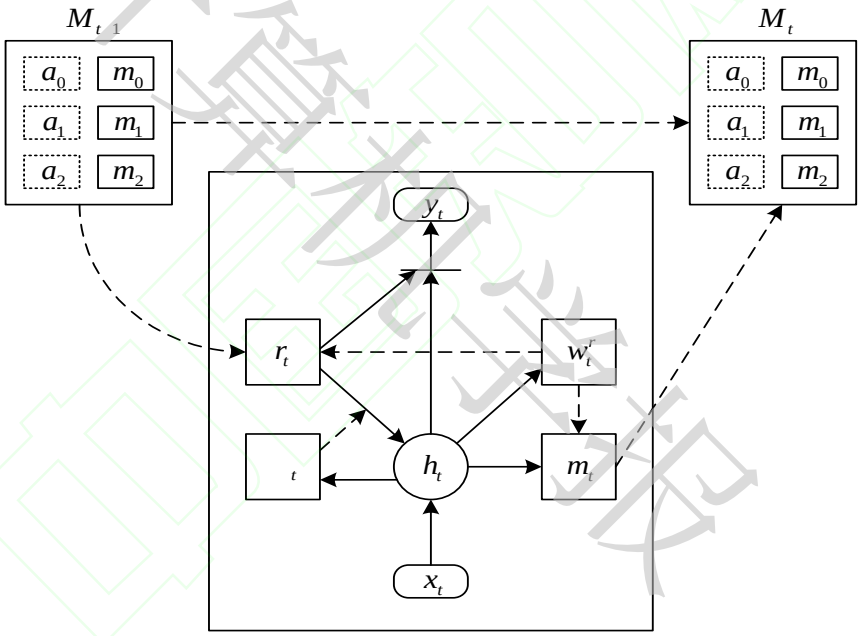
y

adam [63]

3.4.3

Gulcehre Temporal Automatic Relation Discovery In Sequences TARDIS [64]

TARDIS



29 TARDIS

TARDIS 29

h_t

M_t RNN

r_t x_t

w_t^r M_t

$h_{t\ 1}$ h_t $(x_t, h_{t\ 1}, r_t)$

r_t $(M_t)^T w_t^r$ TARDIS

$M_t[i]$ $W_m h_t$

TARDIS

TARDIS M_t LSTM c_t

$A_t \hat{I} \; ¡^{k' a}$ $C_t \hat{I} \; ¡^{k' c}$

$M_t \quad [A_t; C_t] \; \square^{k \; (c \quad a)}$

3.4.4

Sarthak Jain [65]

$\overline{w}_t^r$

$_t[i] \quad a^T \tanh(W_h h_t \quad W_x x_t \quad W_m M_t[i] \quad W_u u_t)$ Freebase

$\overline{w}_t^r \quad \text{soft}\max(\ _t)$ n n-gram n

123 L

$\{a, W_h^g, W_x^g, W_m^g, W_u^g$

$w_t^r \qquad \overline{w}_t^r \qquad \arg\max \overline{w}_t^r$

u_t 1 $F = \{f_1, \text{L}\ , f_{|F|}\}$

$f \qquad (s, R, o) \qquad R \qquad s \qquad o$

$u_t = \text{norm}(\sum_{i=1}^{t-1} w_i^r)$ 124 2 $q \hat{I} \; ¡^{d}$

u_t $f \hat{I} \; F$

TARDIS TARDIS LSTM $g(f) \qquad h(f)$

Gumbel-sigmoid LSTM c_t $g(f)$

$\tilde{c}_t \quad \tanh(\ _t W_h^g h_{t\ 1} \quad W_x^g x_t \quad _t W_r^g r_t)$

$c_t \quad f_t c_{t\ 1} \quad i_t \tilde{c}_t$ 125 $q \quad (s, R) \qquad g(f) \quad q^T(s \quad R)$

$h_t \quad o_t \tanh(c_t)$

softmax $h(f)$

f_t, i_t, o_t LSTM $h(f)$

a_t, b_t

$F = \{f_1, \mathrm{L}\ , f_{|F|}\}$ q

1

2 $f = (s, R, o)$

q

q q $h(f)(s \quad R)$ 126

$f \ F$

3 f

o

f F

q

$h(f)$

$$L_{QA} = \sum_{(q,A)}^{L} \frac{n}{L} \left\| |F_n| \quad a - |A| \quad h(f) ? o \right\|^2$$

127

D -

q A

n n L

o

a $h(f)$

3.4.5

Rae

Sparse Access

Memory SAM [66]

N SAM

$(\log N)$

(N) (1)

SAM

1

$$\tilde{r}_t \sum_{i\ 1}^{K} \tilde{w}_t^R(s_i) M_t(s_i) \quad 128$$

$\tilde{w}_t^R$ $s_1, \mathrm{L}\ , s_K$

w_t^R K

0 K

q K

Approximate nearest neighbors ANN

$\tilde{w}_t^R$

2

$$w_t^W \quad {}_t(\ {}_t w_{t\ 1}^R \quad (1 \quad {}_t) I_t^U) \quad 129$$

t t

$w_{t\ 1}^R$

I_t^U 0

K

I_t^U

U 1 0

$$U_T^{(1)}(i)=\sum_{t=0}^{T} l^{T-t}(w_t^W(i)+w_t^R(i)) \qquad 130$$

r_t LSTM

l

y_t

$$U_T^{(2)}(i)=T-\max\{t: w_t^W(i)+w_t^R(i)>d\} \qquad 3.4.6$$

NTM

131

d Zhang

3 LSTM

[67]

LSTM x_t

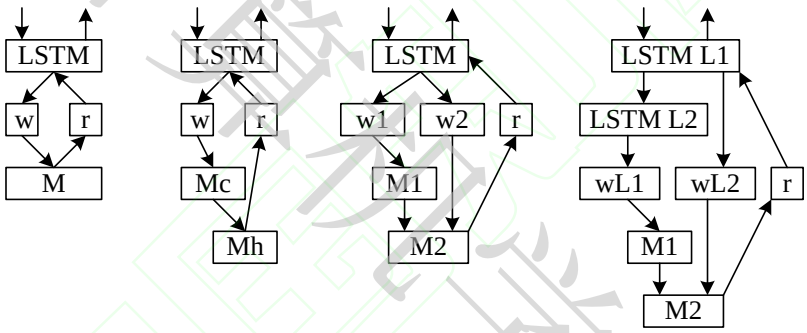
r_{t-1}

Zhang

$p_t=(q_t,a_t,a_t,g_t)$ NTM NTM1 NTM1 NTM1

30

NTM NTM1 NTM2 NTM3



30 NTM

1 NTM1 NTM

M_h t

M_h M_h

$r(t)$ $c(t)$ h

M_c M_h

M_c a b $M_h(t)$

t NTM1

2 NTM2 M_1 M_2

$$M_c(t)=h(M_c(t-1),w(t-1),c(t))$$
$$M_h(t)=aM_h(t-1)+bM_c(t) \qquad 132$$
$$r(t)=w_r(t)M_h(t)$$

M_2 w_2

M_c $t-1$ $w(t-1)$ M_1 w_1

t

M_2 M_1 w_2 NTM2

$$
\begin{aligned}
&M_1(t), w_1(t) = h(M_1(t-1), w_1(t-1), c(t)) \\
&\tilde{M}_2(t), w_2(t) = h(M_2(t-1), w_2(t-1), c(t)) \\
&M_2(t) = a\tilde{M}_2(t) + bM_1(t) \\
&r(t) = w_r(t)M_2(t)
\end{aligned}
\qquad 133
$$

M_1 M_2

M_2

3 NTM3

Luyang Li
[71]

Tang D
[78]

LSTM

Jianpeng Cheng LSTM
[39]

Chen P
[79]

Machine Comprehension

Tran N

Pan LSTM[81] LSTM
[73]

Full-orientation matching

4.2

Hamid Palangi LSTM
[74]

Xu Jia
[82]

LSTM

LSTM

Web

- Arnav Kumar Jain
[54]

Sun - -

J
[80]

Chunseong Park C
[83]
Context Sequence Memory Network CSMN

Instagram

Mingxuan Wang
RNN [75]

Oriol Vinyals
[40]

Ganhotra
[76]

Adam Santoro
[32]

Huang RNN -
-
[77]

Wang J
[88]

Donahue J [87] Long-Term Recurrent Convolutional Networks LTRCN LSTM

Caiming Xiong [43] Ma C [84] Kim K M [85] AI

Joel Moniz [86] LSTM

Scene labeling Abdulnabi A H [89] CNN

Kaiser Ł life-long [90] one-shot

Parmar N [91] ImageNet

Fernando T (Memory Augmented Conditional Generative Adversarial Networks, MC-GAN) [92]

4.3

Kim Y B [93] Speaker-Sensitive Dual Memory Networks SSDMN multi-turn slot tagging

Huang C Z A [94]

text-to-speech TTS Naihan Li Tacotron2 TTS [95]

4.4

Parisotto E [96] 2D

Baskar M K [97]

Bornschein J [98]

[99]

Trang Pham DeepCare[100]

Pham T

Prakash A [108]

[101] Condensed Memory

Neural Networks CMNN

Knowledge Tracing

Schwaller P Zhang J -

[109] Dynamic Key-Value Memory Networks

[102] Molecular DKV-MemNN

Transformer MT

Jonathan Woodbridge LSTM

Domain Generate Algorithm DGA

[103] DGA Sprechmann P

DGA

Lee S W

[104]

4.5

Fernando T [105]

9

Zadeh A

[106]

2D

Khan A

[107]

9

	MN Skip-Thought MN DMN KV-MemNN
	MemN2N
	MN
	LSTM
	LSTM
	WTN ANN Evolved Transformer RNN
	MemN2N
	-
	RAN
	LSTM
	LSTM KV-MemNN CSMN LTRCN
	DMN
	MC-GAN
	SSDMN
	Music Transformer
	TTS
2D	
	DeepCare
	CMNN
	Molecular Transformer
	LSTM DGA
	DKV-MemNN

RNN LSTM NTM MN

5

5.1

RNN

LSTM

NTM

MN

RNN

MN
[111]

4

-

- Tishby [112]

[113]

5

5.2

MN

LSTM

6

[23]

1

7

2

3 MN

MN

LSTM MN

9

16

10

CNN

GAN [90]

11

12

13

[100-102] [103] [107]

14

15

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Background

Deep memory network is a general term for neural network models with memory function, which is mainly to solve the prediction problem of sequence-dependent dependence, and can be predicted by memorizing the effective information learned before. Memory network usually have independent memory modules or other structures capable of memory function. The former stores important information in an independently readable and writable memory and reads it when needed;while the latter method usually modify the internal structure of the cell to retain the information that needs to be remembered.

Deep memory network have achieved unprecedented performance in a wide variety of different application areas. For example, image classification, face recognition, human-level concept learning, playing Atari games and AlphaGo.

Deep memory network combines the benefits of memory network and deep learning. On one hand, memory network has a wider scope of applicability since it can enhance the memory of the model. On the other hand, deep learning can extract a good representation at different levels of abstraction, which disentangles better the factors of variations underlying the data.

In this paper we aim to survey and place in dg AJT befd[(m)17(e)-10()]T