Recurrent Neural Network Based Language Model
+
Character-Aware Neural Language Model

AI LAB
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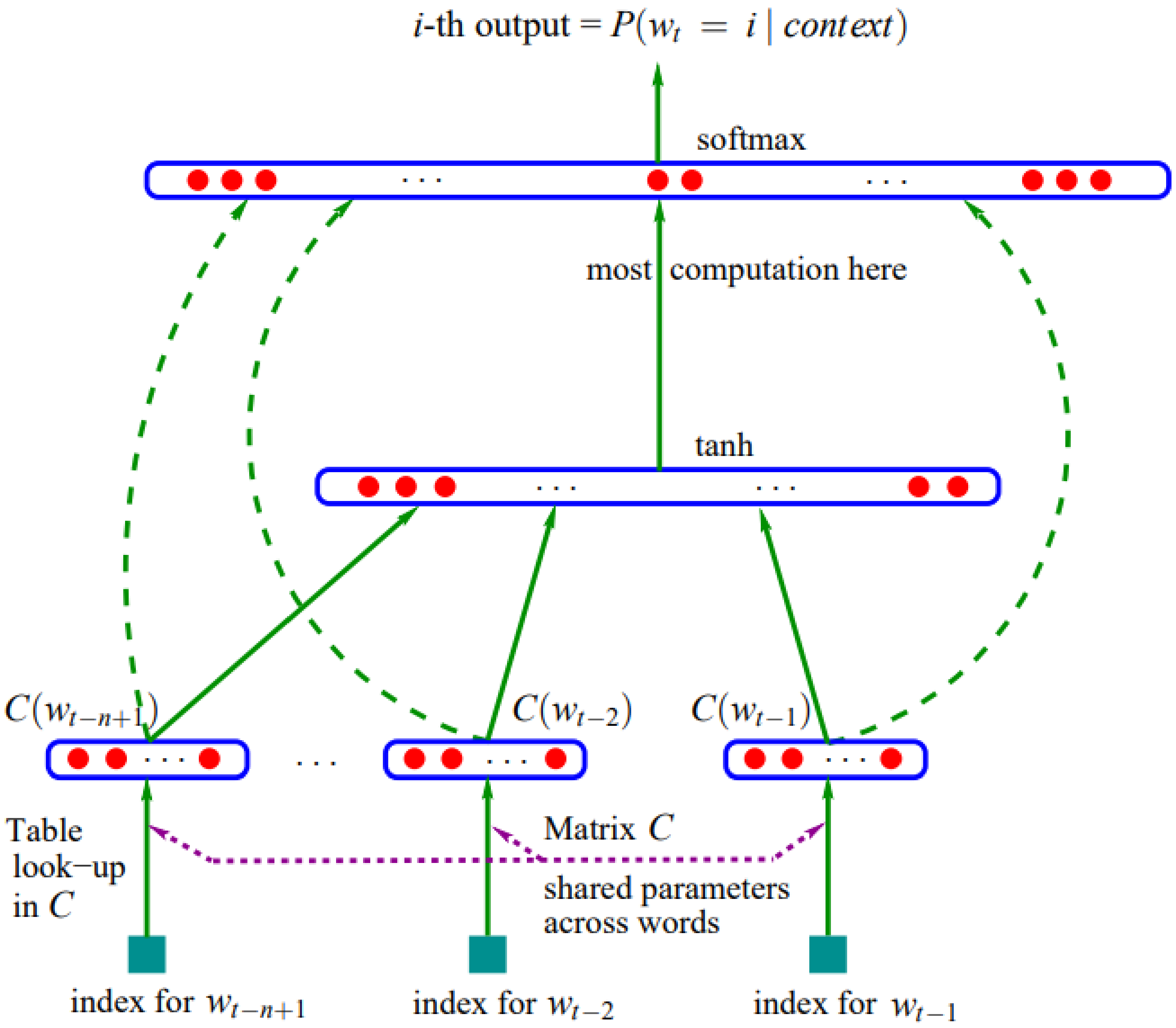
Statistical Language Model : Language domain에 제한적이다.
(몇가지 가정을 전제로 한다!)
N-gram statistic model(가장 널리 쓰이는 모델)조차도 가정이 쪼금 필요하다.

여태까지 등장한 model들은 특정 training data에서만 잘 동작하고, 복잡하며,
N-gram에 비해 tiny improvement만 있었다 + 잘 쓰지도 않는다

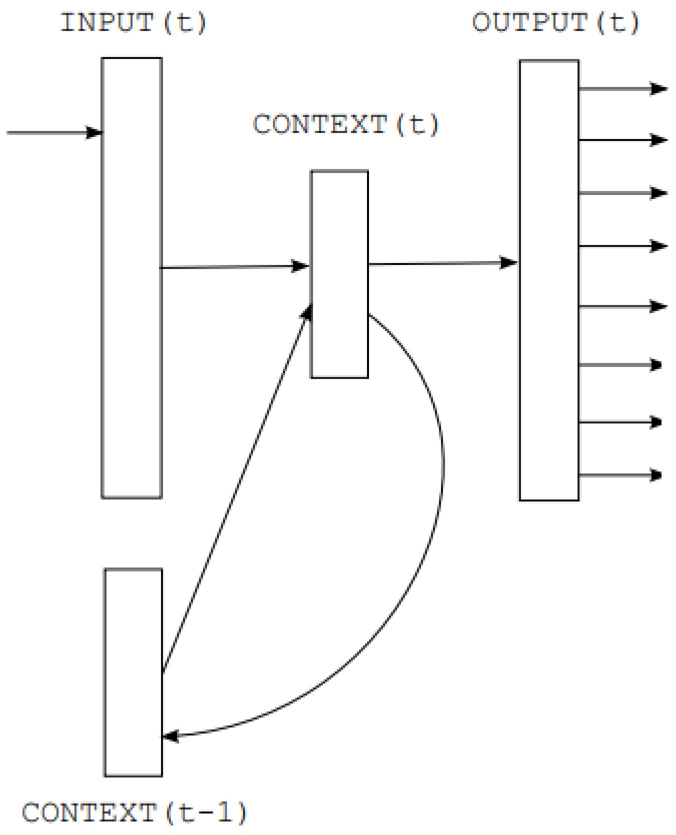


Bengio's Model
(Feedforward Neural Network
with **fixed length** context)

-> 5~10번째 전의 단어들만으로
다음 단어를 판단한다

-> context가 가변적이지 못하다!

RNN을 써보자!
RNN Language Model



$$x(t) = w(t) + s(t-1) \quad (1)$$

$$s_j(t) = f\left(\sum_i x_i(t) u_{ji}\right) \quad (2)$$

$$y_k(t) = g\left(\sum_j s_j(t) v_{kj}\right) \quad (3)$$

where $f(z)$ is sigmoid activation function:

$$f(z) = \frac{1}{1+e^{-z}} \quad (4)$$

and $g(z)$ is softmax function:

$$g(z_m) = \frac{e^{z_m}}{\sum_k e^{z_k}} \quad (5)$$

$$\mathrm{error}(t) = \mathrm{desired}(t) - y(t) \quad (6)$$

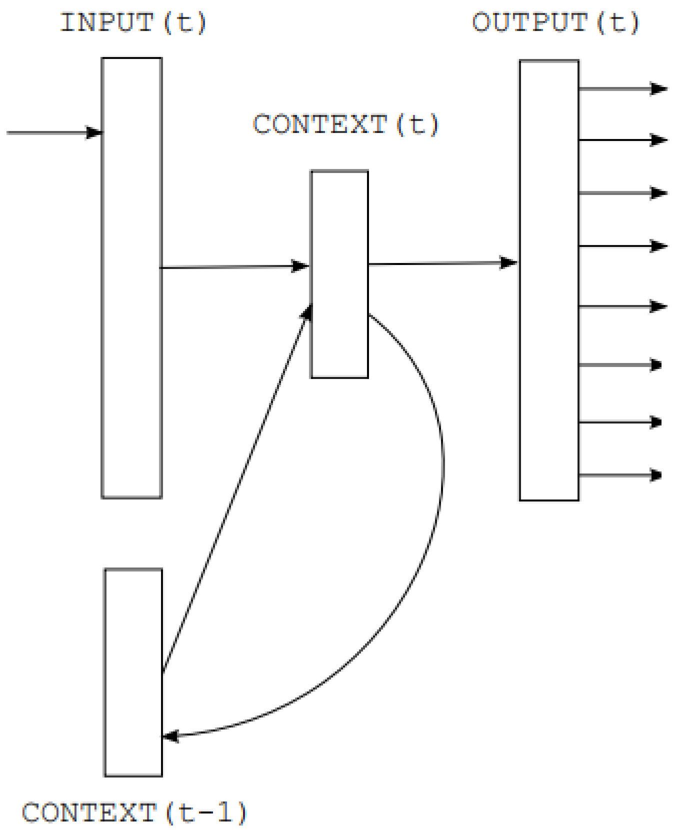
x – input layer (1-of-N encoding vector)
s – hidden layer (or context or state)
y – output layer
w – word vector

w의 size – vocabulary size(3만~20만)
s의 size – 30~500
(data 크기에 영향을 받는다)

Weight – standard backpropagation

Parameter의 개수가 줄어듬
(FNN – layer/hidden size, context-length
RNN – hidden layer size 하나만!)

Hidden layer가 컸는데도
Overtrain이 잘 안됨!(띠용)



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Statistical Model에서는
test data에서의 model update를 하지 않았다
(사람이름 등등에서 문제 발생!)

-> **Dynamic model**
Long term memory가 전체 synapse 안에 상주한다
(test pharse에서도 학습이 된다!)

Traning phase에서는 매 epoch마다 update
Dynamic model은 test data를 이용해 1번만!

전혀 Optimal하지 않음
근데 효과가 좋음;

Word-probabilities

$$P(w_i(t+1)|w(t), s(t-1)) = \begin{cases} \frac{y_{rare}(t)}{C_{rare}} & \text{if } w_i(t+1) \text{ is rare,} \\ y_i(t) & \text{otherwise} \end{cases} \quad (7)$$

Optimization(성능을 올려보자)

Special Rare Token!
-training data의 단어들 사이에서 rare한 단어들을 하나의 special rare token으로 merge
(rare의 기준은 threshold)

C_{rare} : threshold를 못 넘은 단어의 개수

모든 rare 단어들의 확률은
Uniform distribution

그래서 잘됨?

Table 1: *Performance of models on WSJ DEV set when increasing size of training data.*

Model	# words	PPL	WER
KN5 LM	200K	336	16.4
KN5 LM + RNN 90/2	200K	271	15.4
KN5 LM	1M	287	15.1
KN5 LM + RNN 90/2	1M	225	14.0
KN5 LM	6.4M	221	13.5
KN5 LM + RNN 250/5	6.4M	156	11.7

Table 2: *Comparison of various configurations of RNN LMs and combinations with backoff models while using 6.4M words in training data (WSJ DEV).*

	PPL		WER	
Model	RNN	RNN+KN	RNN	RNN+KN
KN5 - baseline	-	221	-	13.5
RNN 60/20	229	186	13.2	12.6
RNN 90/10	202	173	12.8	12.2
RNN 250/5	173	155	12.3	11.7
RNN 250/2	176	156	12.0	11.9
RNN 400/10	171	152	12.5	12.1
3xRNN static	151	143	11.6	11.3
3xRNN dynamic	128	121	11.3	11.1

ㅇㅇ 잘됨

(PPL – perplexity (낮을수록좋다)
WER – Word Error Rate)

KN(Kneser-Ney smoothed n-gram)

Data의 수가 더 적었음에도 기존 모델보다 성능이 더 좋더라!

특수한 가정이 필요하지 않아서 쉽게 적용할 수 있다!

Voca 사이즈가 클수록 성능이 좋아진다!

짱짱

But!

Word-embedding(대표적으론 One-hot vector)에는 단어 정보가 담기지 않아요!
-> 빈도수가 적은 단어에 대한 PPL이 높아짐(성능 떡락)
-> 형태소가 많은 언어에서 특히 문제!

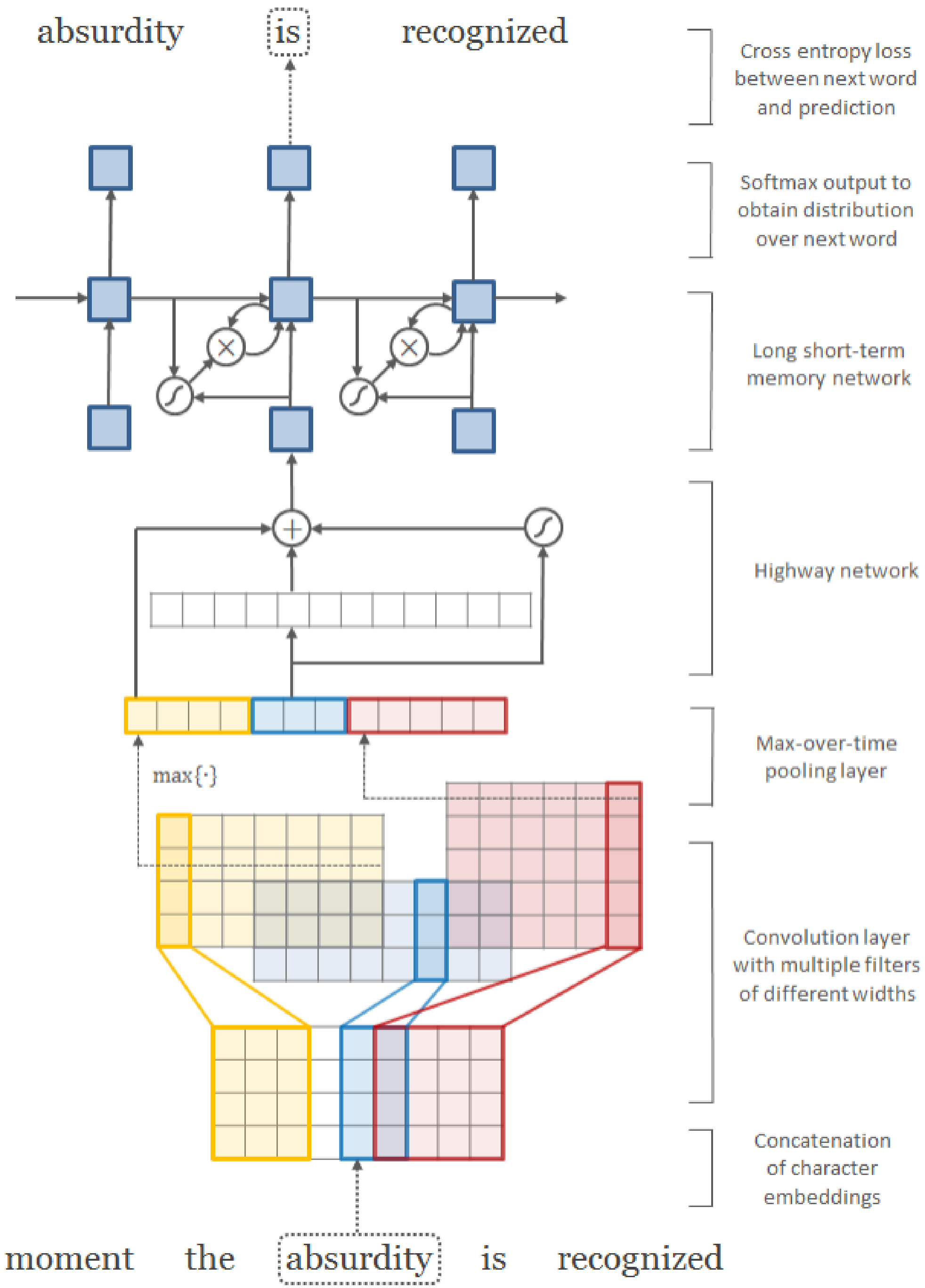
Character-Aware
Neural Language Model

선요약 후설명

charCNN을 통한 subword information 학습을 시도해보았다!

그랬더니 parameter가 더 적어도 다른 모델보다 더 좋더라!

짱짱


absurdity
is
recognized
Cross entropy loss between next word and prediction
Softmax output to obtain distribution over next word
Long short-term memory network
Highway network
Max-over-time pooling layer
max{·}
Convolution layer with multiple filters of different widths
Concatenation of character embeddings
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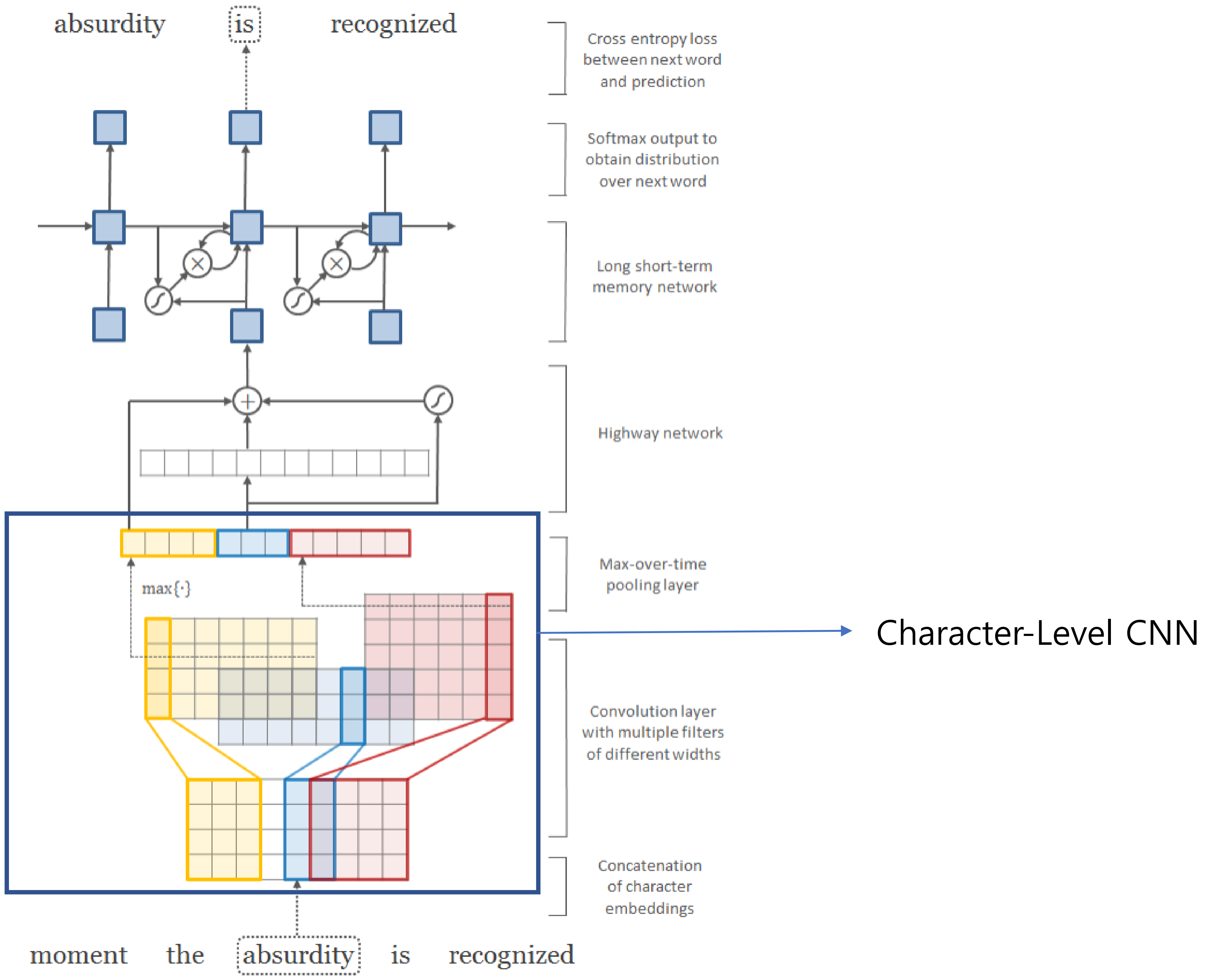
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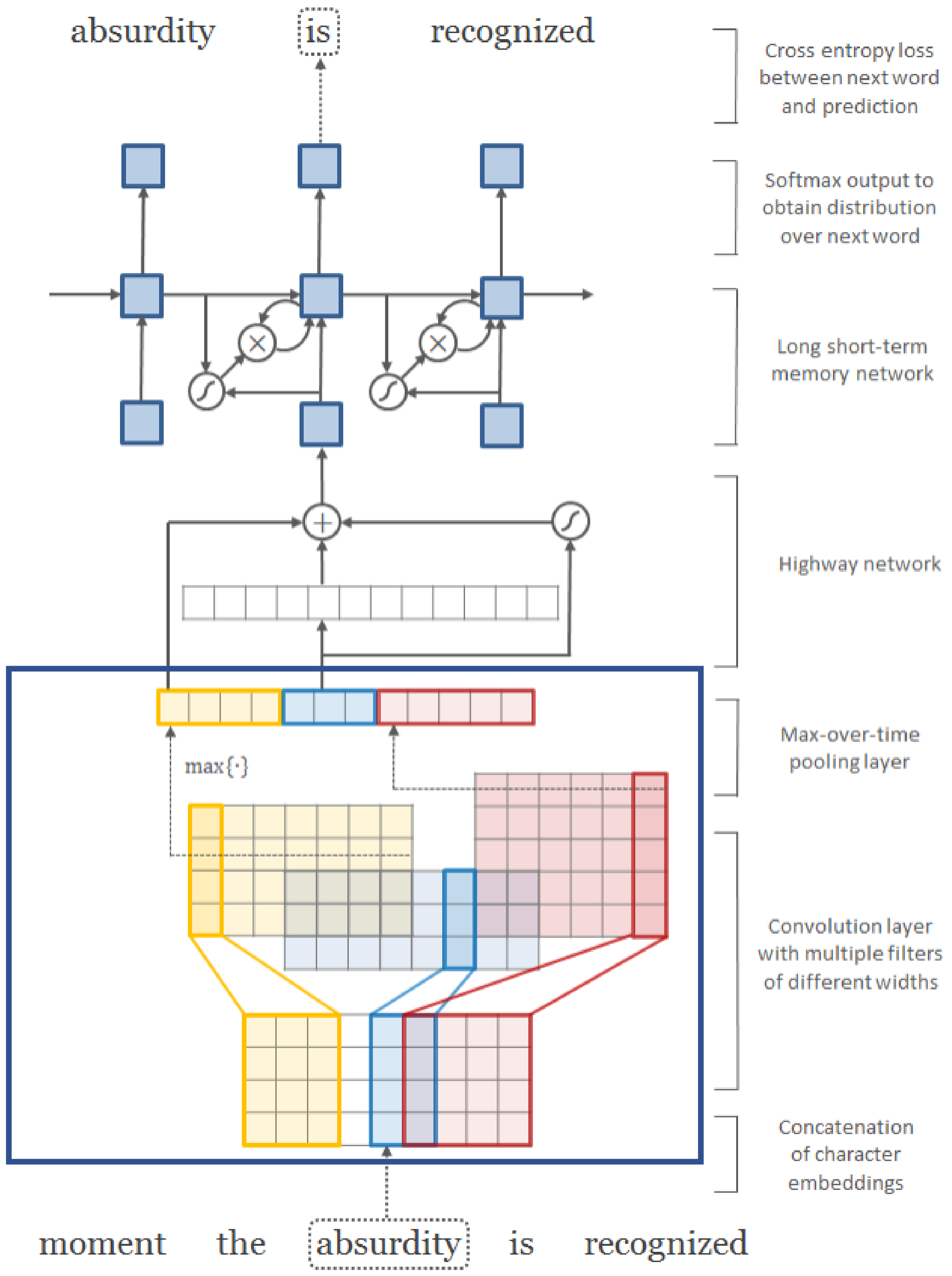
Character-Level CNN



Character-Level CNN

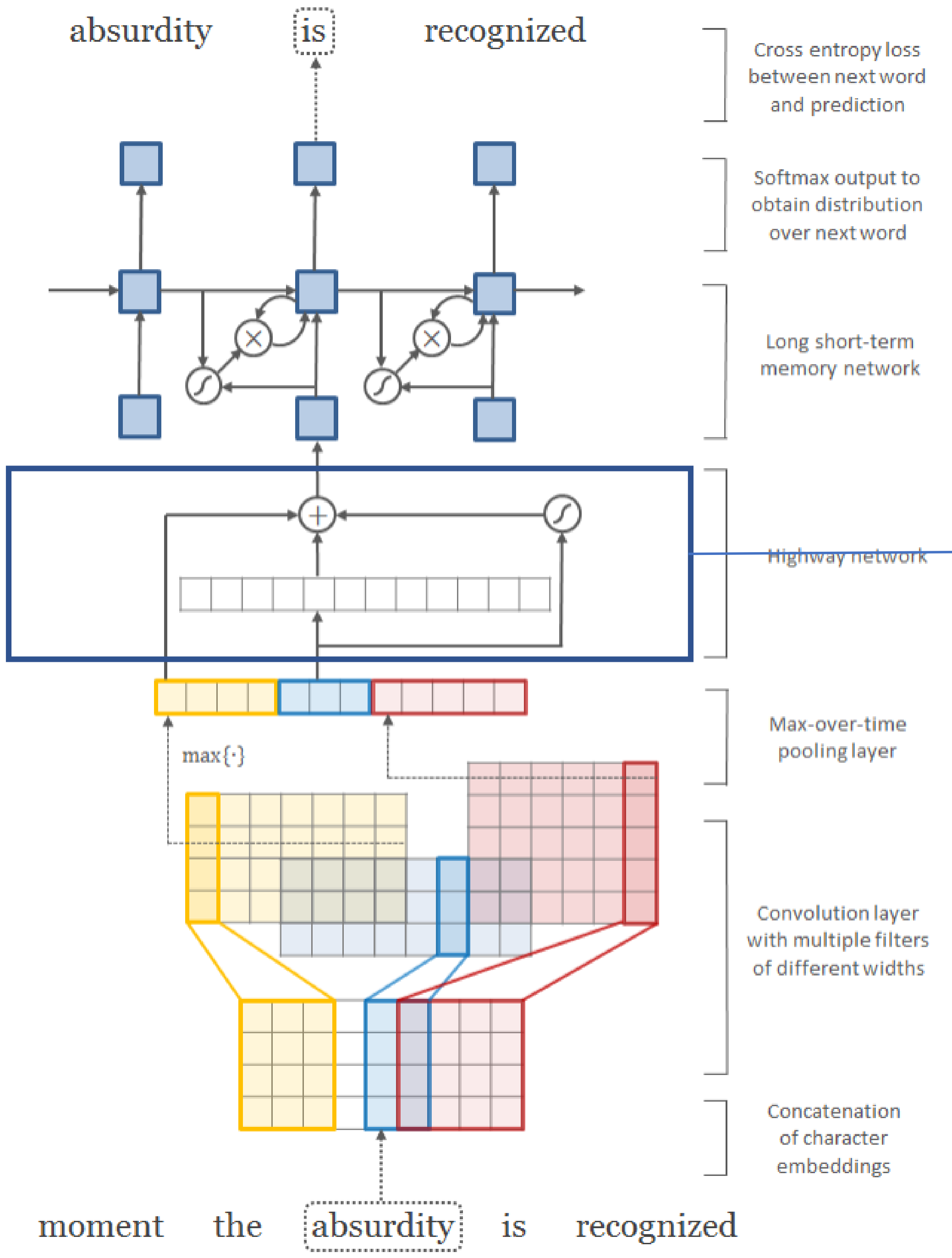
단어(char)로 이루어진 word를 CNN에 넣는다!
(word = sequence of character)

filter의 개수는 보통 [100,1000] 사이

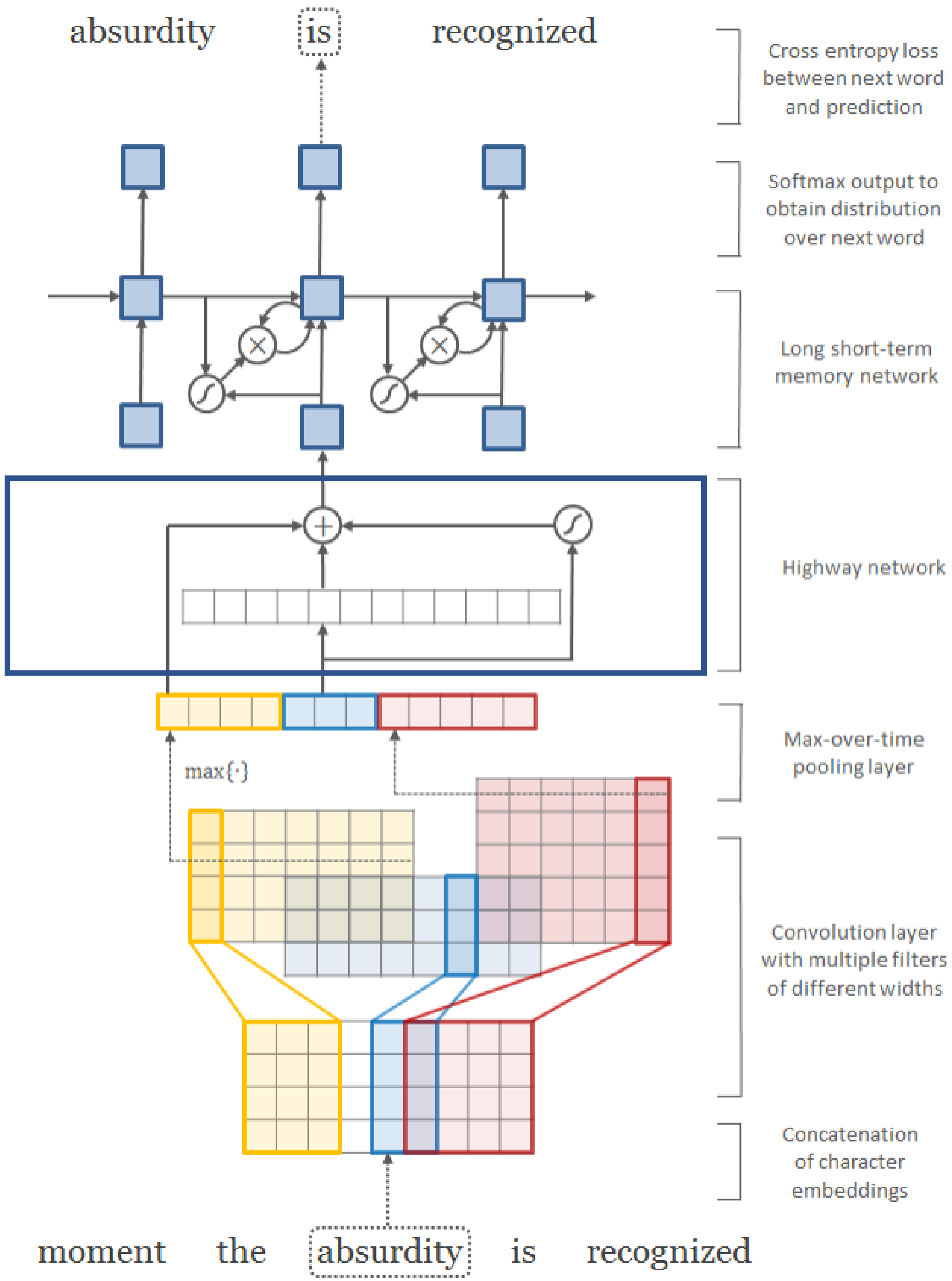
filtering 자체가 n-gram의 역할을 한다

결과물을 max-over-time pooling

-> Word embedding같은 효과!



Highway Network



Highway Network

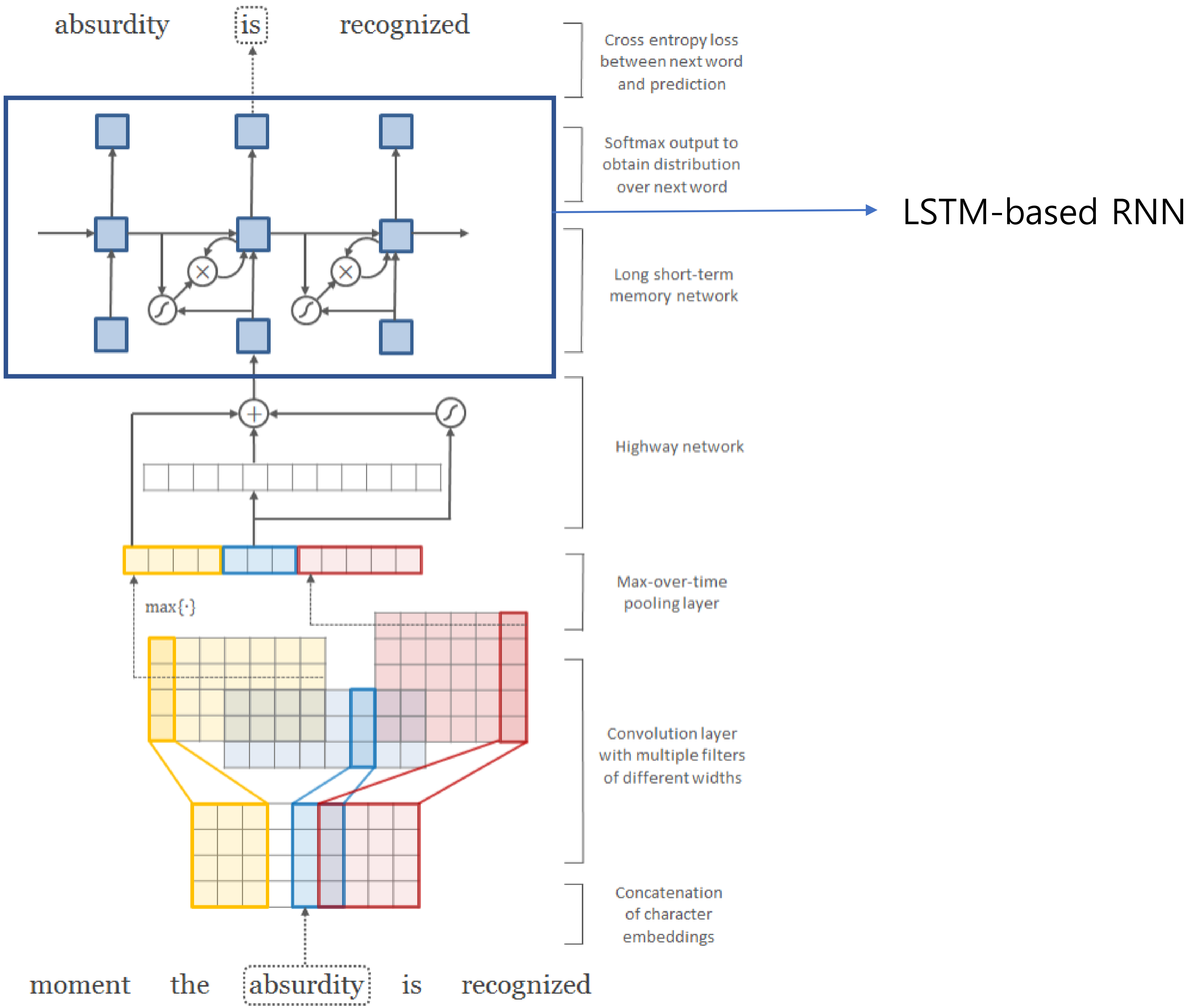
※Residual Network(ResNet)
모든 layer를 거치지 않고 일부 layer만을 거치는 방법

Model interaction에 사용
(원래는 MLP를 써봤는데 구리더라!)

$$\mathbf{z} = \mathbf{t} \odot g(\mathbf{W}_H \mathbf{y} + \mathbf{b}_H) + (\mathbf{1} - \mathbf{t}) \odot \mathbf{y} \qquad (8)$$

$$\mathbf{t} = \sigma(\mathbf{W}_T \mathbf{y} + \mathbf{b}_T)$$

t = transform gate / (1-t) = carry gate
-> LSTM의 memory cell과 비슷하지 않은감?
-> 특정 dimension을 다음 network에
그대로 carry하는 역할을 한다



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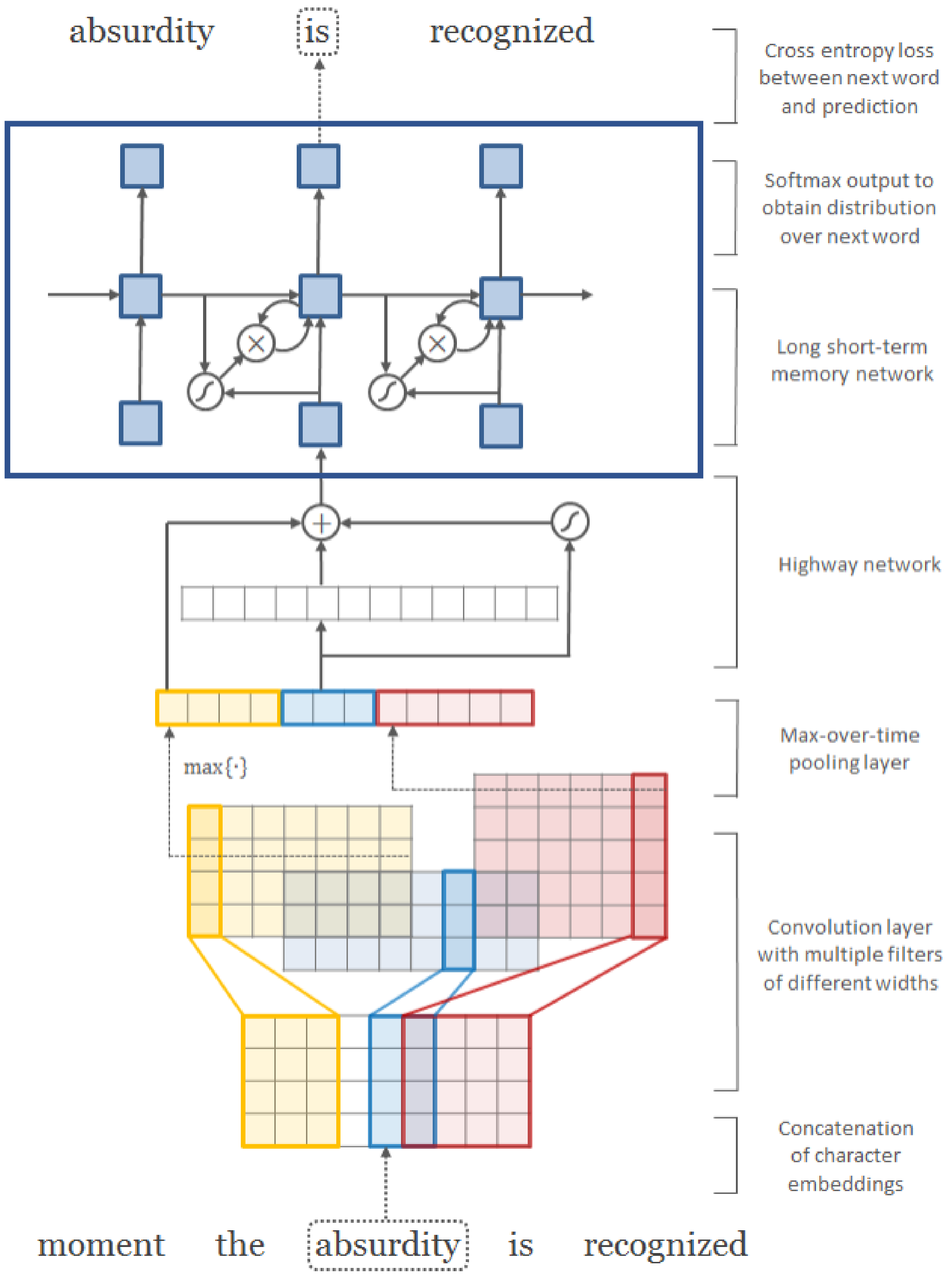

요긴 그냥 특별할것없는 LSTM

Language Model이니까 당연히 RNN보단 LSTM

$$\Pr(w_{t+1} = j | w_{1:t}) = \frac{\exp(\mathbf{h}_t \cdot \mathbf{p}^j + q^j)}{\sum_{j' \in \mathcal{V}} \exp(\mathbf{h}_t \cdot \mathbf{p}^{j'} + q^{j'})} \quad (3)$$

Negative log-likelihood를 최소하는 방향으로 학습

$$NLL = -\sum_{t=1}^{T} \log \Pr(w_t | w_{1:t-1}) \quad (4)$$

그래서 잘됨?

	PPL	Size
LSTM-Word-Small	97.6	5 m
LSTM-Char-Small	92.3	5 m
LSTM-Word-Large	85.4	20 m
LSTM-Char-Large	78.9	19 m
KN-5 (Mikolov et al. 2012)	141.2	2 m
RNN† (Mikolov et al. 2012)	124.7	6 m
RNN-LDA† (Mikolov et al. 2012)	113.7	7 m
genCNN† (Wang et al. 2015)	116.4	8 m
FOFE-FNNLM† (Zhang et al. 2015)	108.0	6 m
Deep RNN (Pascanu et al. 2013)	107.5	6 m
Sum-Prod Net† (Cheng et al. 2014)	100.0	5 m
LSTM-1† (Zaremba et al. 2014)	82.7	20 m
LSTM-2† (Zaremba et al. 2014)	78.4	52 m

English Penn Treebank

		Small	Large
CNN	d	15	15
	w	$[1, 2, 3, 4, 5, 6]$	$[1, 2, 3, 4, 5, 6, 7]$
	h	$[25 \cdot w]$	$[\min\{200, 50 \cdot w\}]$
	f	tanh	tanh
Highway	l	1	2
	g	ReLU	ReLU
LSTM	l	2	2
	m	300	650

d = dimensionality of character embedding
w = filter width
h = number of filter matrix
f , g = 비선형 function
l = number of layers
m = number of hidden units

ㅇㅇ 잘됨

PPL – perplexity (낮을수록좋다)

KN(Kneser-Ney smoothed n-gram)

Word-level model들의 OOV들은
unknown token으로 replace되었음에도
우리꺼가 parameter 수(Size) 대비 성능이 쩐다!

	In Vocabulary					Out-of-Vocabulary		
	while	*his*	*you*	*richard*	*trading*	*computer-aided*	*misinformed*	*looooook*
LSTM-Word	*although*	*your*	*conservatives*	*jonathan*	*advertised*	–	–	–
	letting	*her*	*we*	*robert*	*advertising*	–	–	–
	though	*my*	*guys*	*neil*	*turnover*	–	–	–
	minute	*their*	*i*	*nancy*	*turnover*	–	–	–
LSTM-Char (before highway)	*chile*	*this*	*your*	*hard*	*heading*	*computer-guided*	*informed*	*look*
	whole	*hhs*	*young*	*rich*	*training*	*computerized*	*performed*	*cook*
	meanwhile	*is*	*four*	*richer*	*reading*	*disk-drive*	*transformed*	*looks*
	white	*has*	*youth*	*richter*	*leading*	*computer*	*inform*	*shook*
LSTM-Char (after highway)	*meanwhile*	*hhs*	*we*	*eduard*	*trade*	*computer-guided*	*informed*	*look*
	whole	*this*	*your*	*gerard*	*training*	*computer-driven*	*performed*	*looks*
	though	*their*	*doug*	*edward*	*traded*	*computerized*	*outperformed*	*looked*
	nevertheless	*your*	*i*	*carl*	*trader*	*computer*	*transformed*	*looking*

Word embedding 학습도 잘하더라!
OOV word도 학습하더라!
짱짱

charCNN을 쓰면 접두사/접미사/하이픈을 더 잘 구분한다

Corpus가 커질수록 성능도 더 좋아지더라

word embedding이랑 같이 쓰니까 성능이 더 안좋아지더라…?
(POS tagging이랑 NER이랑 같이쓴거는 성능 좋던데..?)
-> 우리쪽에선 쓸데없나봄

charCNN layer를 공유하다보니 GPU 사용효율성이 증가하더라

ㄲㅡㅌ