



Introduction



Introduction



Related Work



Model



Experiments



Conclusion

Recurrent Convolutional Neural Network for Text Classification

• AAAI 2015에서 발표된 논문

- 제목만 봐도 대충 무슨 내용인지 알 듯한……...
 - Recurrent Convolutional Neural Network 를 이용해서
 - Text Classification 이라는 문제를 해결해보겠다!



Text Classification



Introduction



Related Work



Model



Experiments



Conclusion

• Text Classification 문제를 풀고자 함

- Text Classification이란?
 - 제일 베이직한 NLP task 중 하나
 - Input으로 text (sentence, paragraph)를 받아서, Output으로 Classification 결과를 내보냄
 - 주제 분류 (Topic Classification), 감정 분석 (Sentiment Analysis) 등이 이에 해당됨



Related Work



Introduction



Related Work



Model



Experiments



- Traditional Method
 - Feature Engineering
 - Feature Selection
 - Machine Learning Model

- Neural Method
 - Convolutional Neural Network
 - Recurrent Neural Network





Introduction



Related Work



Model



Experiments



Conclusion

• 좋은 Feature를 만들어보자!

- 좋은 Feature로는 무엇이 있을까요?
 - Bag-of-words
 - N-gram
 - NLP toolkit





Introduction



Related Work



Model



Experiments



Conclusion

Bag-of-words

A: I will play the game after seminar

B: Let's play the soccer after seminar



Sentence	i	play	seminar	let's	will	the	after	game	soccer
А	1	1	1	0	1	1	1	1	0
В	0	1	1	1	0	1	1	0	1

자연어 문장 → Feature Vector

변환시킨 vector를 model의 input으로 넣는다





Introduction



Related Work



Model



Experiments



Conclusion

N-gram

A: I will play the game after seminar

• B: Let's play the soccer after seminar



Sentence	i	play	•••	i will	will play	play the	•••	soccer after	after seminar
А	1	1	•••	1	1	1	•••	0	1
В	0	1	•••	0	0	1	•••	1	1





Introduction



Related Work



Model



Experiments



Conclusion

- N-gram
 - A sunset stroll along the South **Bank** affords an array of stunning vantage points.
 - 위 문장에서 *Bank* 의 뜻이 무엇일까?
 - 1-gram (uni-gram) : 은행, 둑
 - 2-gram (bi-gram) : 남쪽 은행, 둑...?
 - 5-gram (five-gram) : 런던의 지방 이름 South Bank

Sentence	a	sunset	•••	South Bank	Bank affords	•••	Stroll along the South Bank	•••
А	1	1	•••	1	1	•••	1	•••

N을 키우면 문맥 정보를 보다 많이 얻을 수 있지만
Data Sparsity 문제가 생김





Introduction



Related Work



Model



Experiments



- NLP Toolkit
 - POS Parser
 - Dependency Parser
 - NER tagger
- 과거 연구에는 필수적인 Feature로 사용되었음
- 하지만 NLP Toolkit 자체가 많은 에러를 포함하고 있고, 이를 ML model에 넣고 학습하면 에러가 더욱 증폭됨
- 최근에는 이런 NLP Toolkit에 의한 Feature 없이, 순수 raw sentence만을 가지고 model을 학습시키고자 함



Traditional Method - Feature Selection & ML Model



Introduction



Related Work



Model



Experiments



- Feature Selection
 - Feature들 중 쓸모 있는 것들을 추려내는 작업
 - ex) stop-word
- Machine Learning Model
 - Logistic Regression
 - Naïve Bayes Classifier
 - Support Vector Machine



Neural Method



Introduction



Related Work



Model

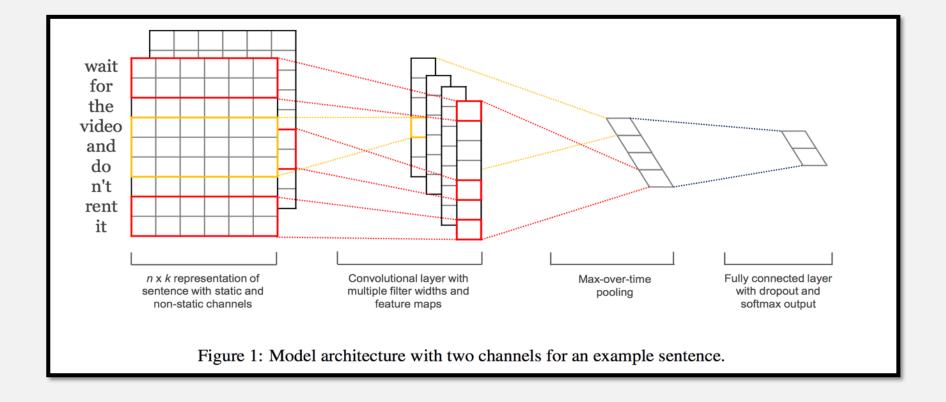


Experiments



Conclusion

Convolutional Neural Network





Neural Method



Introduction



Related Work



Model

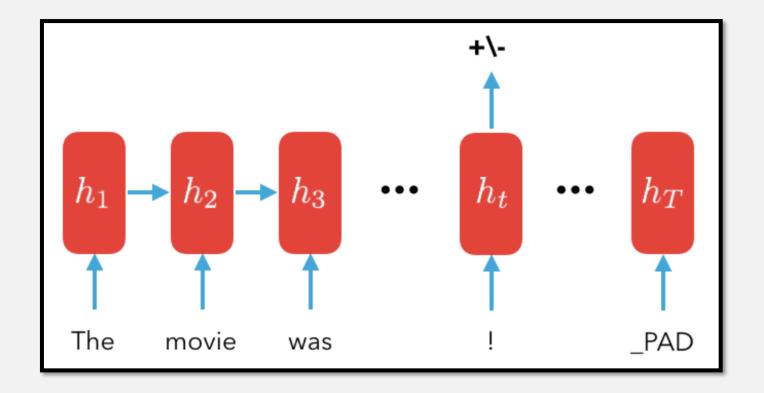


Experiments



Conclusion

Recurrent Neural Network







Introduction



Related Work

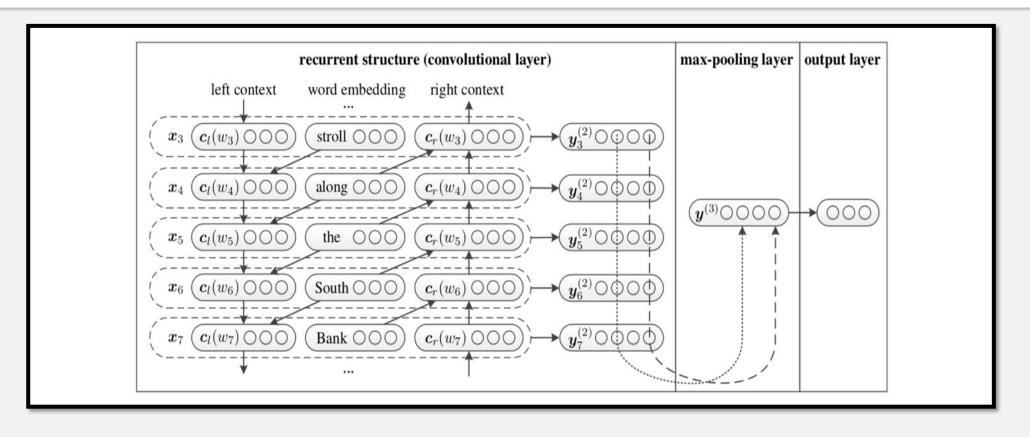


Model



Experiments





- Recurrent Structure 를 이용하여
- Context Embeddings 을 하고
- 이를 이용해 Convolution 을 모사했더니, 기존 CNN 보다 좋았다!





Introduction



Related Work

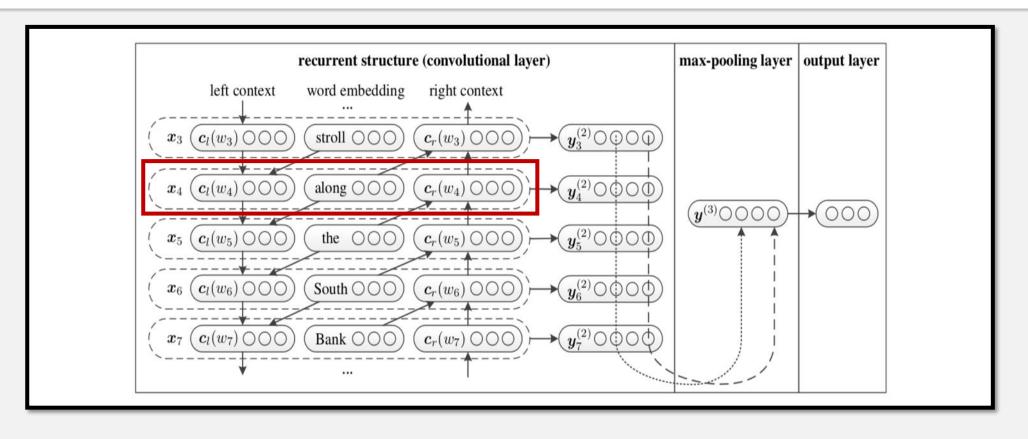


Model



Experiments





- Word Representation: 하나의 단어는 x_i 로 표현함
 - $x_i = [c_l(w_i); e(w_i); c_r(w_i)]$
 - $c_l(\cdot)$ and $c_r(\cdot)$ is context embeddings,
 - $e(\cdot)$ is word embeddings





Introduction



Related Work



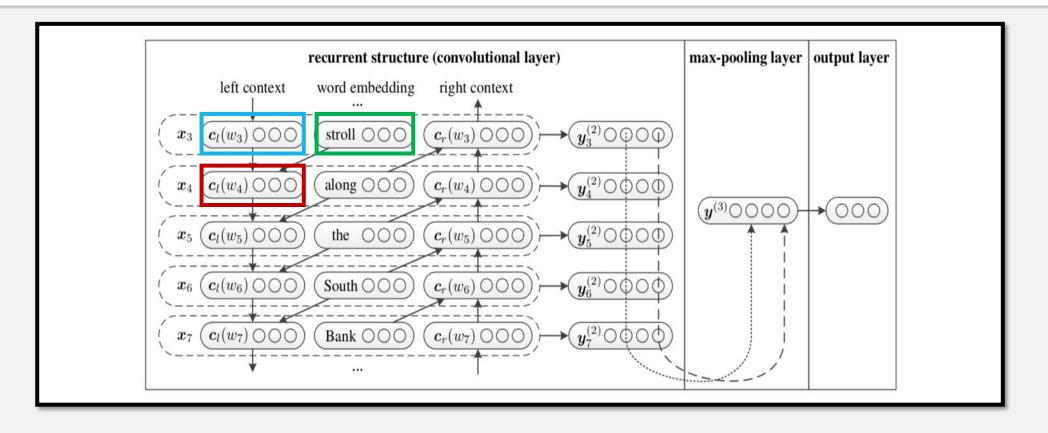
Model



Experiments



Conclusion



Context Embeddings

$$c_l(w_i) = f(W^{(l)}c_l(w_{i-1}) + W^{(sl)}e(w_{i-1})$$





Introduction



Related Work



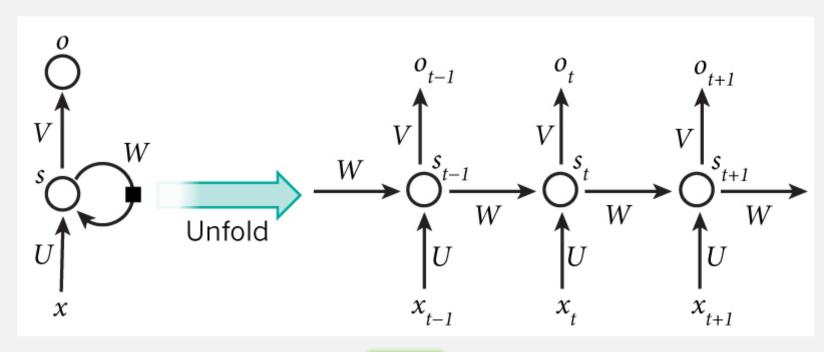
Model



Experiments



Conclusion



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

Context Embeddings

$$c_l(w_i) = f(W^{(l)}c_l(w_{i-1}) + W^{(sl)}e(w_{i-1})$$





Introduction



Related Work

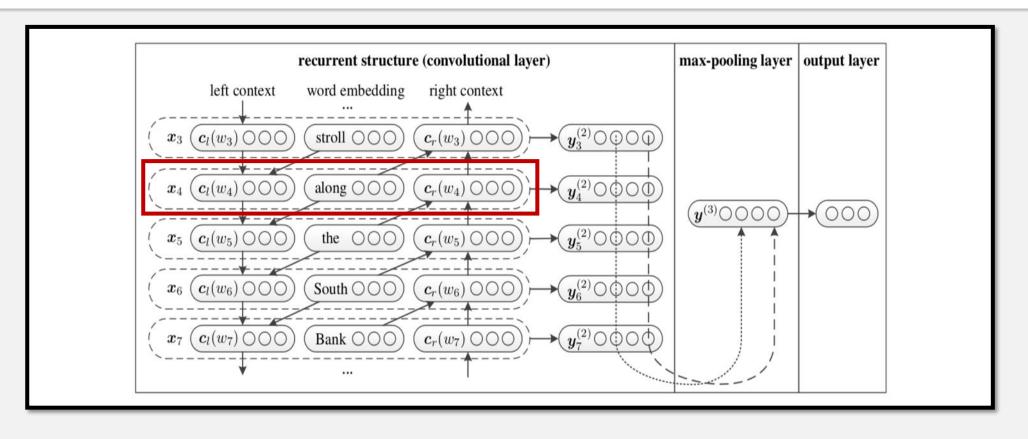


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Experiments





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Introduction



Related Work



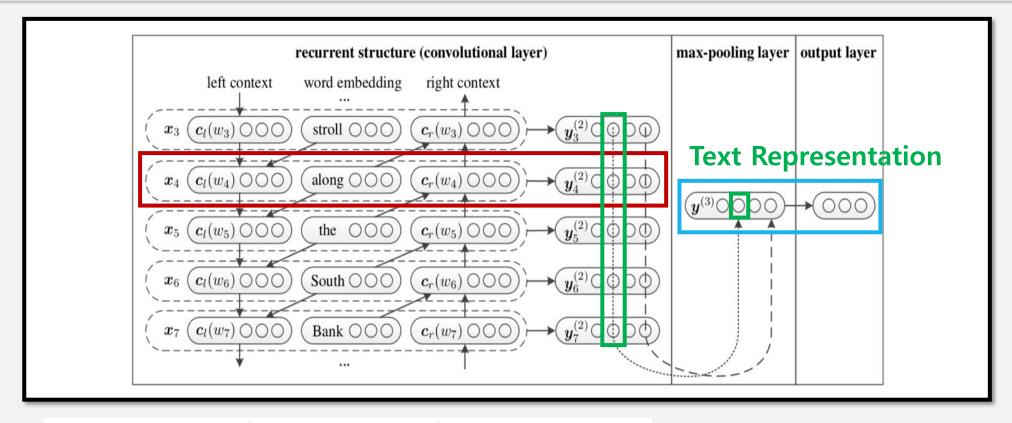
Model



Experiments



Conclusion



$$\boldsymbol{y}_i^{(2)} = \tanh\left(W^{(2)}\boldsymbol{x}_i + \boldsymbol{b}^{(2)}\right) \tag{4}$$

$$\mathbf{y}^{(3)} = \max_{i=1}^{n} \mathbf{y}_{i}^{(2)} \tag{5}$$

$$\mathbf{y}^{(4)} = W^{(4)}\mathbf{y}^{(3)} + \mathbf{b}^{(4)} \tag{6}$$

• 이후 아키텍처는 매우 심플함



Comparison with CNN



Introduction



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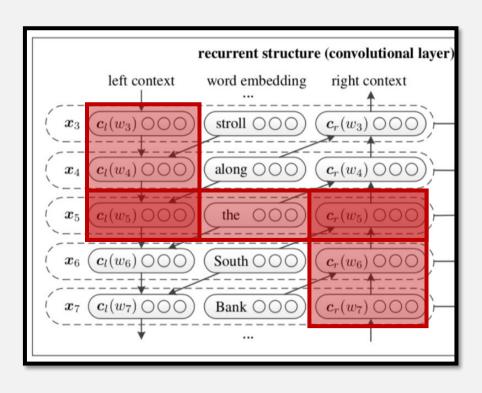


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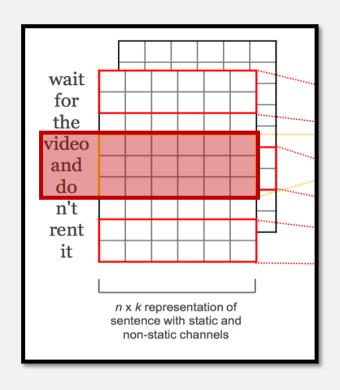


Experiments





Recurrent Convolutional NN



Convolutional NN

- CNN은 window size 만큼의 context 정보만 사용
- RCNN은 앞 뒤 전체의 context 정보를 사용





Introduction



Related Work

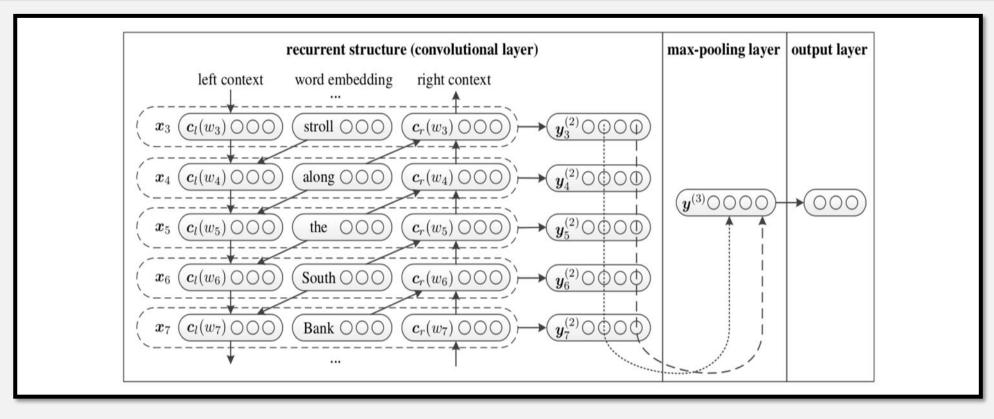


Model



Experiments





- 결론적으로,
- CNN도 아닌, RNN도 아닌 혼종...
- RNN 구조를 이용해, 기존 CNN의 window based Convolution보다 문맥 정보를 잘 활용하는 모델을 제안 (근데 이름을 이렇게 짓다니...)



Experiments



Introduction



Related Work



Model



Experiments



Conclusion

Model	20News	Fudan	ACL	SST
BoW + LR	92.81	92.08	46.67	40.86
Bigram + LR	93.12	92.97	47.00	36.24
BoW + SVM	92.43	93.02	45.24	40.70
Bigram + SVM	92.32	93.03	46.14	36.61
Average Embedding	89.39	86.89	41.32	32.70
ClassifyLDA-EM (Hingmire et al. 2013)	93.60	_	-	-
Labeled-LDA (Li, Sun, and Zhang 2008)	_	90.80	_	_
CFG (Post and Bergsma 2013)	_	-	39.20	_
C&J (Post and Bergsma 2013)	_	-	49.20	-
RecursiveNN (Socher et al. 2011b)	_	_	_	43.20
RNTN (Socher et al. 2013)	_	_	_	45.70
Paragraph-Vector (Le and Mikolov 2014)	-	-	-	48.70
CNN	94.79	94.04	47.47	46.35
RCNN	96.49	95.20	49.19	47.21

• 당연한 얘기지만, 다른 모델보다 성능이 잘 나온다고 함





Introduction



Related Work



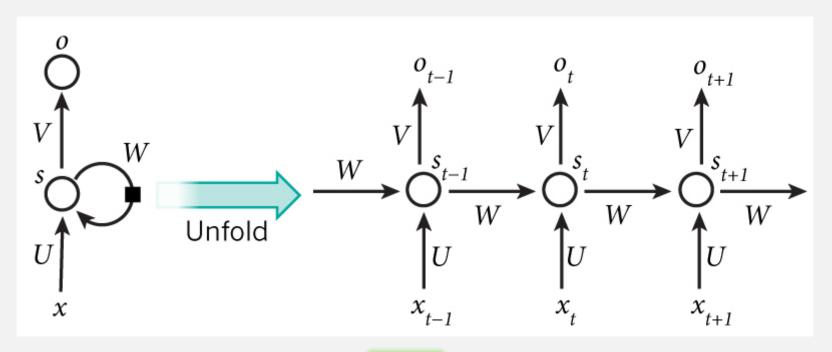
Model



Experiments



Conclusion



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Introduction



Related Work

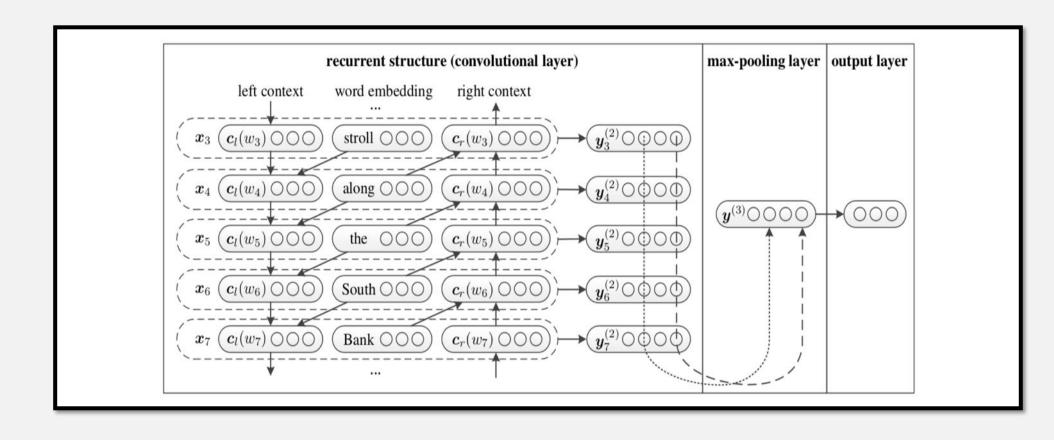


Model



Experiments





- 구현해보려고 했으나, 당최 어떻게 해야 할 지 감이 오지 않음
- 특히, recurrent structure...





Introduction



Related Work



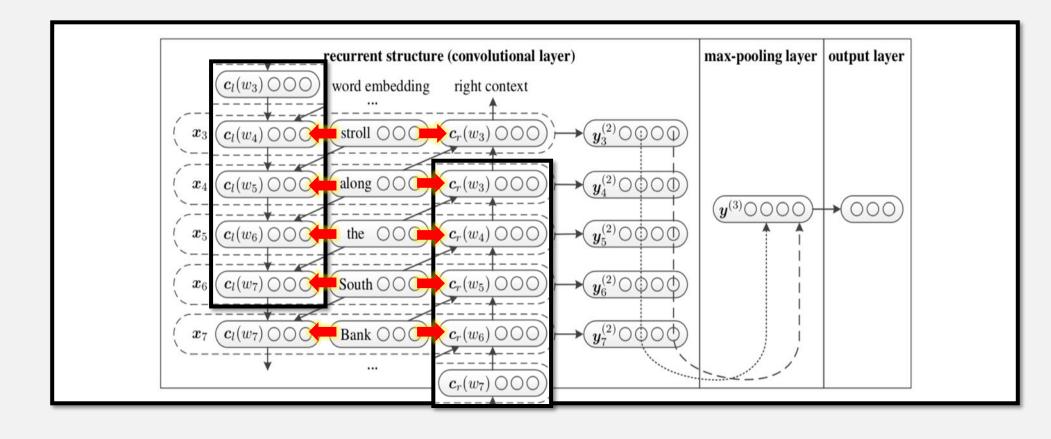
Model



Experiments



Conclusion



• 일반 RNN을 위와 같이 구성하여 output (state)를 취함





Introduction



Related Work



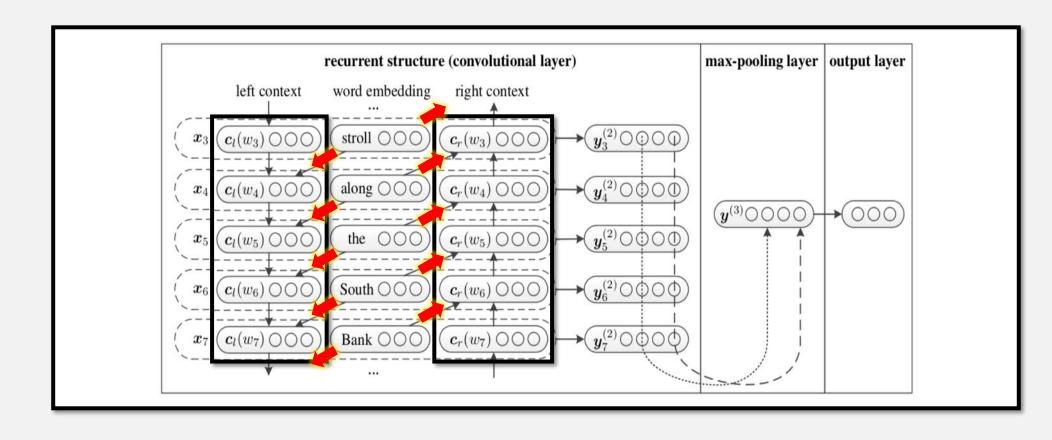
Model



Experiments



Conclusion



Output과 word embedding을 합칠 때,
 output을 한 칸(cell)씩 밀어서 concatenate하면 완성!



Discussion



Introduction



Related Work



Model



Experiments



```
well worth the; a wonderful movie; even stinging at;

P and invigorating film; and ingenious entertainment; and enjoy .; 's sweetest movie

A dreadful live-action; Extremely boring .; is n't a;

N 's painful .; Extremely dumb .; an awfully derivative; 's weaker than; incredibly dull .; very bad sign;
```

- Max-pooling 할 때, 선택되는 단어를 뽑아봄
- Classification 하는데 큰 영향을 준 단어라고 보면 될 듯
- 나름 그럴싸한 단어를 잘 찾아내는 것으로 보임



Conclusion & Future Work



Introduction



Related Work



Model



Experiments



- Conclusion (Contribution)
 - CNN보다 문맥 정보를 잘 활용하는 RNN 기반의 Network을 제안
 - CNN이 문맥정보를 잘 활용하지 못한다는 것을 보여줌

- Future Work
 - Recurrent structure로 convolution을 모사한 부분 이외에는 너무나도 심플하기 때문에 뒷 구조를 보강하면 성능을 높일 수 있지 싶음
 - 저자가 제안한 Network을 기반으로 다양한 NLP task에 적용
 - 지금 하고 있는 Relation Extraction 에도 적용시켜보려 함

