# SpatialNet: A Declarative Resource for Spatial Relations

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# Main Work

- This paper introduces SpatialNet, a novel resource which links linguistic expressions to actual spatial configurations.

- SpatialNet is based on FrameNet and VigNet, two resources which use frame semantics to encode lexical

- In this paper, we describe the structureof SpatialNet, with examples from English and German. We also show how SpatialNet can be combined with other existing NLP tools to create a text-to-scene system for a language.

# Case

In our first example, English *on* is correctly translated to German *an*:[1]

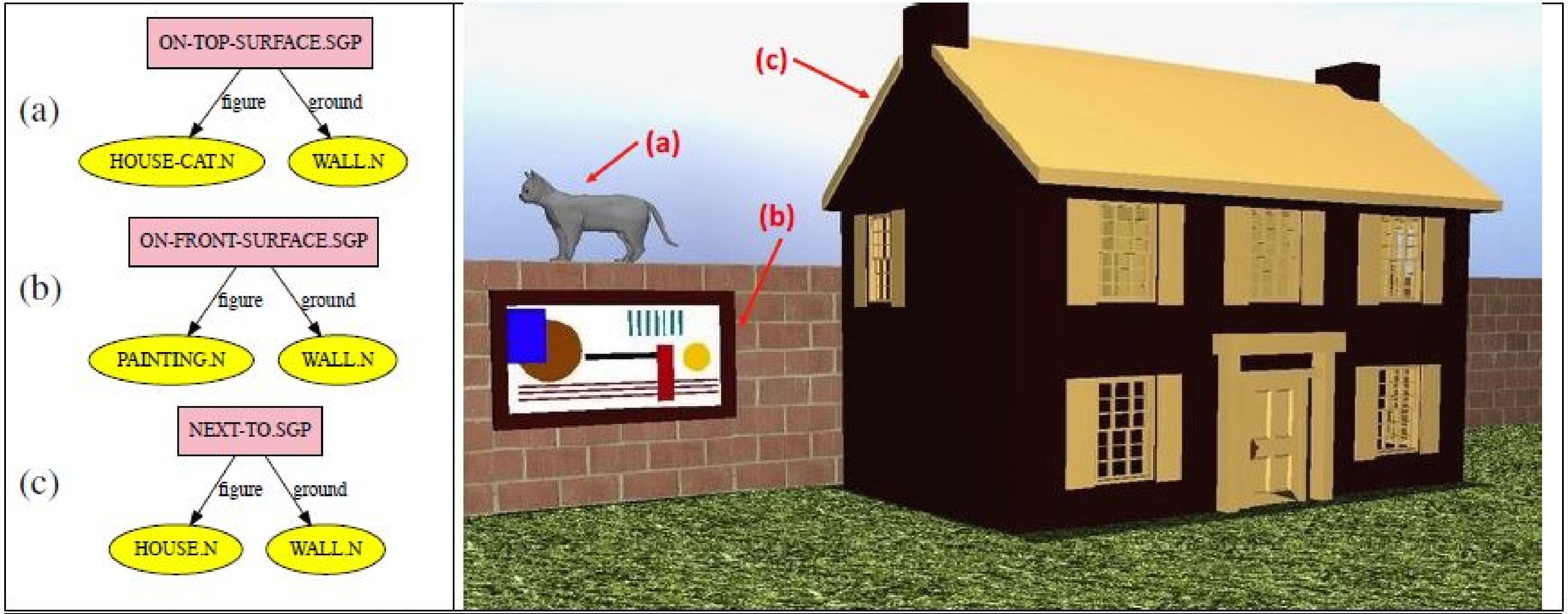
(1) a. The painting **on** the wall is abstract.
  b. Correct translation: Das Gemälde **an** der Mauer/Wand ist abstrakt.
  c. Google Translate/Bing Translator (correct): Das Gemälde **an** der Wand ist abstrakt.

However, the correct translation changes if we are relating a cat to a wall:

(2) a. The cat **on** the wall is grey.
  b. Correct translation: Die Katze **auf** der Mauer ist grau.
  c. Google Translate/Bing Translator (incorrect): Die Katze **an** der Wand ist grau.

The problem here is that the English preposition *on* describes two different spatial configurations: 'affixed to', in the case of the painting, and 'on top of', in the case of the cat.[2]

# Case




| | (a) | (b) | (c) |
|---|---|---|---|
| **English** | *The cat is on the wall.* | *The painting is on the wall.* | *The house is at the wall.* |
| **German** | *Die Katze ist auf der Mauer.* | *Das Gemälde ist an der Mauer.* | *Das Haus ist an der Mauer.* |

Figure 2: Examples of spatio-graphic primitives: (a) ON-TOP-SURFACE, (b) ON-FRONT-SURFACE, and (c) NEXT-TO and English/German descriptions.

# SpatialNet

- **Spatio graphic primitives (SGPs)**
  Represent possible graphical (spatial) relations.

- **Ontology**
  Represents physical objects and their classification into semantic categories.

# Case

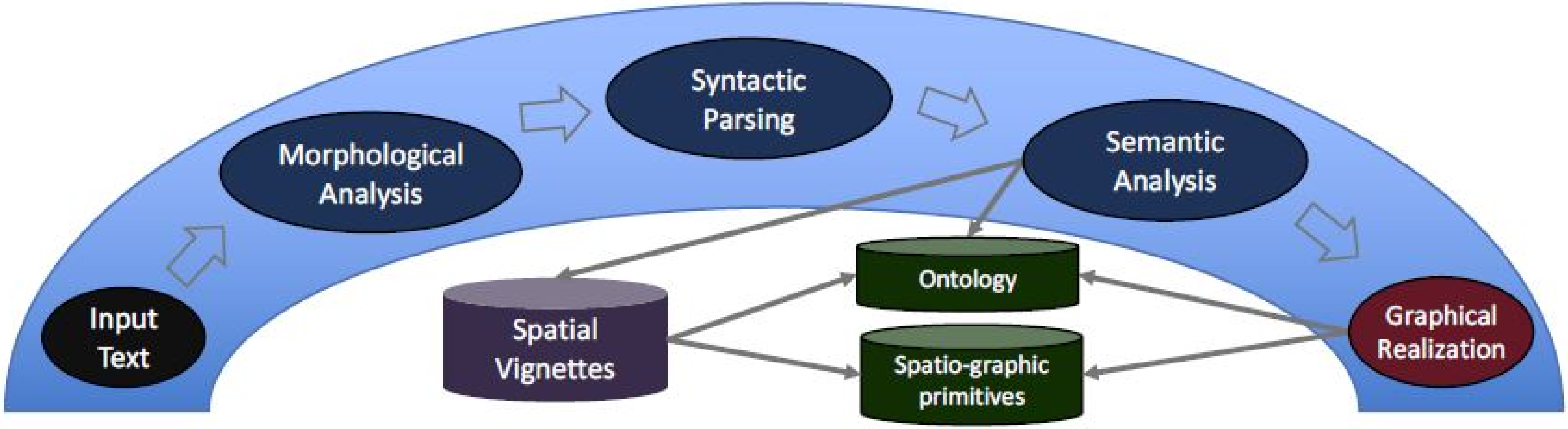



Figure 5: Pipeline for text-to-scene generation with SpatialNet

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# Self-Attention Enhanced Selective Gate with Entity-Aware Embedding for Distantly Supervised Relation Extraction


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# Motivation

- Distantly supervised relation extraction intrinsically suffers from noisy labels due to the strong assumption of distant supervision
- Most prior works adopt a selective attention mechanism over sentences in a bag to denoise from wrongly labeled data, which however could be incompetent when there is only one sentence in a bag
- we propose a brand-new light-weight neural framework to address the distantly supervised relation extraction problem and alleviate the defects in previous selective attention framework

# Case

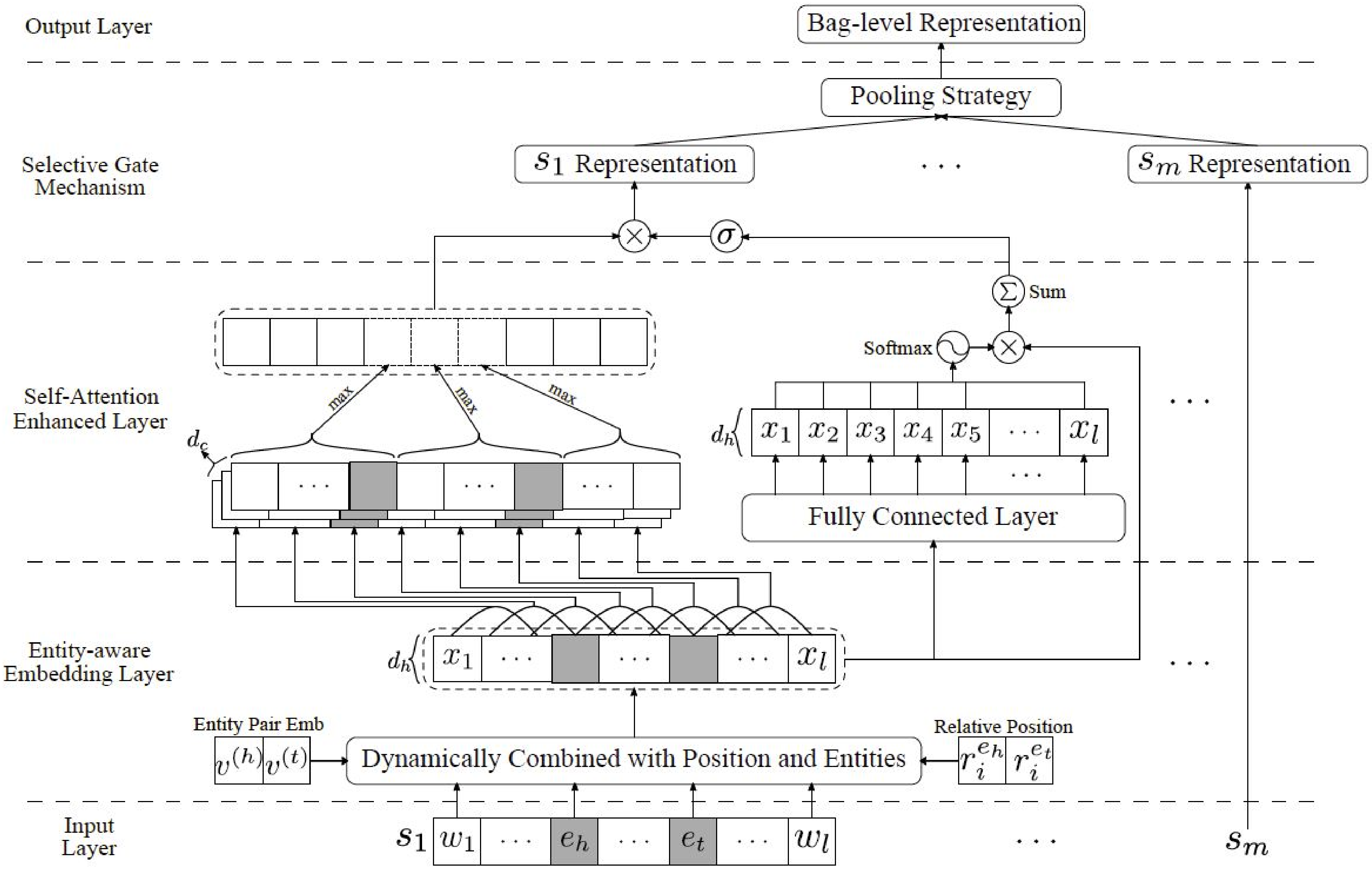
| Bag consisting of one sentence | Label | Correct |
|---|---|---|
| After moving back to *New York*, *Miriam* was the victim of a seemingly racially motivated attack ... | place_lived | True |
| ... he faced, walking *Bill Mueller* and giving up singles to Mark Bellhorn and *Johnny Damon*. | place_lived | False |

Table 1: Two examples of one-sentence bag, which are correctly and wrongly labeled by distant supervision respectively.

# NYT dataset

- For NYT dataset (Riedel, Yao, and McCallum2010), up to 80% of its training examples (i.e., bags) are **one-sentence** bags
- From our data inspection, we randomly sample 100 one-sentence bags and find 35% of them is incorrectly labeled
- These results indicate that, in training phrase the selective attention module is enforced to output a single-valued scalar for 80% examples, leading to an illtrained attention module and thus hurting the performance

# Model



Output Layer
Bag-level Representation
Pooling Strategy
Selective Gate Mechanism
$s_1$ Representation
$s_m$ Representation
Sum
Softmax
Self-Attention Enhanced Layer
max
max
max
$d_c$
$d_h$
$x_1$ $x_2$ $x_3$ $x_4$ $x_5$ $\cdots$ $x_l$
Fully Connected Layer
Entity-aware Embedding Layer
$x_1$ $\cdots$ $\cdots$ $\cdots$ $x_l$
Entity Pair Emb
$v^{(h)}$ $v^{(t)}$
Dynamically Combined with Position and Entities
Relative Position
$r_i^{e_h}$ $r_i^{e_t}$
Input Layer
$s_1$ $w_1$ $\cdots$ $e_h$ $\cdots$ $e_t$ $\cdots$ $w_l$
$s_m$

# Entity-Aware Embedding

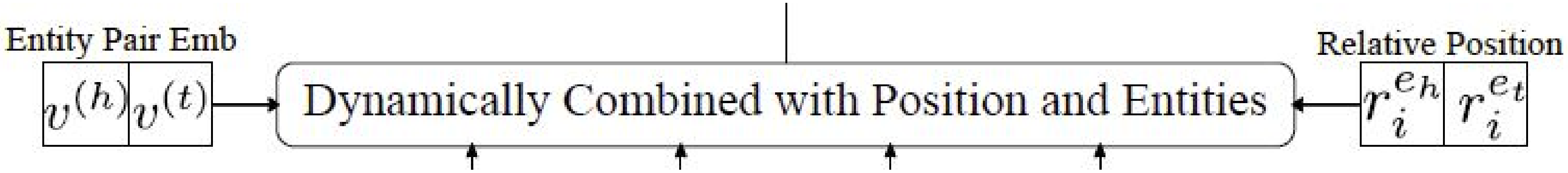
$$\boldsymbol{\alpha} = \mathrm{sigmoid}(\lambda \cdot (\boldsymbol{W}^{(g1)}\boldsymbol{X}^{(e)} + \boldsymbol{b}^{(g1)})),$$

$$\tilde{\boldsymbol{X}}^{(p)} = \tanh(\boldsymbol{W}^{(g2)}\boldsymbol{X}^{(p)} + \boldsymbol{b}^{(g2)}),$$

$$\boldsymbol{X} = \boldsymbol{\alpha} \cdot \boldsymbol{X}^{(e)} + (1 - \boldsymbol{\alpha}) \cdot \tilde{\boldsymbol{X}}^{(p)},$$

$$\text{where, } \boldsymbol{X}^{(e)} = [\boldsymbol{x}_i^{(e)}]_{i=1}^{n}, \ \forall \boldsymbol{x}_i^{(e)} = [\boldsymbol{v}_i; \boldsymbol{v}^{(h)}; \boldsymbol{v}^{(t)}],$$

$$\text{in which } \boldsymbol{x}_i^{(p)} = [\boldsymbol{v}_i; \boldsymbol{r}_i^{e_h}; \boldsymbol{r}_i^{e_t}]$$

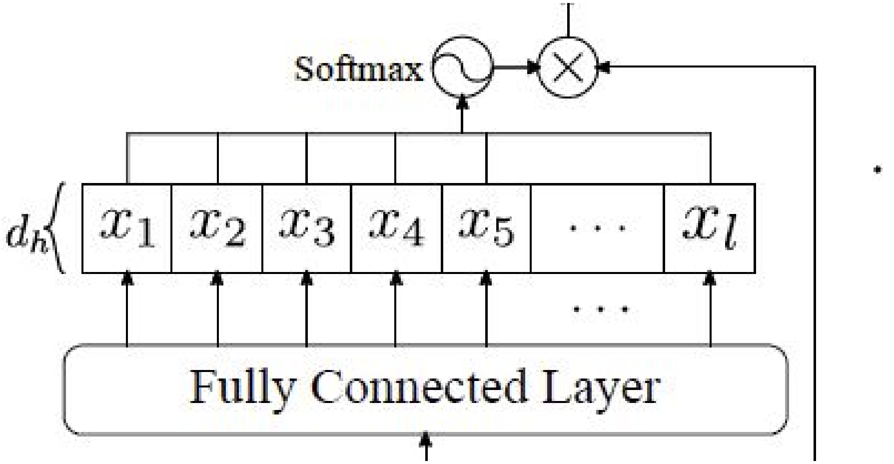


# Self-Attention Mechanism

$$\boldsymbol{A} = \boldsymbol{W}^{(a2)}\sigma(\boldsymbol{W}^{(a1)}\boldsymbol{X} + \boldsymbol{b}^{(a1)}) + \boldsymbol{b}^{(a2)},$$

$$\boldsymbol{P}^{(A)} = \mathrm{softmax}(\boldsymbol{A}),$$

$$\boldsymbol{u} = \sum \boldsymbol{P}^{(A)} \odot \boldsymbol{X}$$



# PCNN

$$\boldsymbol{H} = \text{1D-CNN}(\boldsymbol{X}; \boldsymbol{W}^{(c)}, \boldsymbol{b}^{(c)}) \in \mathbb{R}^{d_c \times n}$$

$$\boldsymbol{s} = \tanh([\text{Pool}(\boldsymbol{H}^{(1)}); \text{Pool}(\boldsymbol{H}^{(2)}); \text{Pool}(\boldsymbol{H}^{(3)})]).$$

# Selective Gate and Output

$$\boldsymbol{S} = [\boldsymbol{s}_1, \ldots, \boldsymbol{s}_m] \qquad \boldsymbol{U} = [\boldsymbol{u}_1, \ldots, \boldsymbol{u}_m]$$

$$g_j = \mathrm{sigmoid}(\boldsymbol{W}^{(g1)} \sigma(\boldsymbol{W}^{(g2)} \boldsymbol{u}_j + \boldsymbol{b}^{(g2)}) + \boldsymbol{b}^{(g1)}), \quad \forall j = 1, \ldots, m,$$

$$\boldsymbol{c} = \frac{1}{m} \sum_{j=1}^{m} g_j \cdot \boldsymbol{s}_j$$

$$\boldsymbol{p} = \mathrm{softmax}(\mathrm{MLP}(\boldsymbol{c})) \in \mathbb{R}^{|C|}.$$

# Result

| **Approach** | **One** | | | | **Two** | | | | **All** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **P@N (%)** | 100 | 200 | 300 | Mean | 100 | 200 | 300 | Mean | 100 | 200 | 300 | Mean |
| *Comparative Approaches* | | | | | | | | | | | | |
| CNN+ATT (Lin et al. 2016) | 72.0 | 67.0 | 59.5 | 66.2 | 75.5 | 69.0 | 63.3 | 69.3 | 74.3 | 71.5 | 64.5 | 70.1 |
| PCNN+ATT (Lin et al. 2016) | 73.3 | 69.2 | 60.8 | 67.8 | 77.2 | 71.6 | 66.1 | 71.6 | 76.2 | 73.1 | 67.4 | 72.2 |
| PCNN+ATT+SL (Liu et al. 2017) | 84.0 | 75.5 | 68.3 | 75.9 | 86.0 | 77.0 | 73.3 | 78.8 | 87.0 | 84.5 | 77.0 | 82.8 |
| PCNN+HATT (Han et al. 2018) | 84.0 | 76.0 | 69.7 | 76.6 | 85.0 | 76.0 | 72.7 | 77.9 | 88.0 | 79.5 | 75.3 | 80.9 |
| PCNN+BAG-ATT (Ye and Ling 2019) | 86.8 | 77.6 | 73.9 | 79.4 | 91.2 | 79.2 | 75.4 | 81.9 | 91.8 | 84.0 | 78.7 | 84.8 |
| **SeG** *(ours)* | **94.0** | **89.0** | **85.0** | **89.3** | **91.0** | **89.0** | **87.0** | **89.0** | **93.0** | **90.0** | **86.0** | **89.3** |
| *Ablations* | | | | | | | | | | | | |
| SeG w/o Ent | 85.0 | 75.0 | 67.0 | 75.6 | 87.0 | 79.0 | 70.0 | 78.6 | 85.0 | 80.0 | 72.0 | 79.0 |
| SeG w/o Gate | 87.0 | 85.5 | 82.7 | 85.1 | 89.0 | 87.0 | 84.0 | 86.7 | 90.0 | 88.0 | 85.3 | 87.7 |
| SeG w/o Gate w/o Self-Attn | 86.0 | 85.0 | 82.0 | 84.3 | 88.0 | 86.0 | 83.0 | 85.7 | 90.0 | 86.5 | 86.0 | 87.5 |
| SeG w/o ALL | 81.0 | 73.5 | 67.3 | 74.0 | 82.0 | 75.0 | 72.3 | 76.4 | 81.0 | 75.0 | 72.0 | 76.0 |
| SeG+ATT w/o Gate | 89.0 | 83.5 | 75.7 | 82.7 | 90.0 | 83.5 | 77.0 | 83.5 | 92.0 | 82.0 | 76.7 | 83.6 |
| SeG+ATT | 88.0 | 81.0 | 75.0 | 81.3 | 87.0 | 82.5 | 77.0 | 82.2 | 90.0 | 86.5 | 81.0 | 85.8 |
| SeG w/ stack | 91.0 | 88.0 | 85.0 | 88.0 | 91.0 | 87.0 | 85.0 | 87.7 | 92.0 | 89.5 | 86.0 | 89.1 |

# Result

| Approach | AUC |
|---|---|
| PCNN+HATT | 0.42 |
| PCNN+ATT-RA+BAG-ATT | 0.42 |
| **SeG** (ours) | 0.51 |

Table 3: Model comparison regarding the AUC value. The comparative results are reported by Han et al. (2018) and Ye and Ling (2019) respectively.

| Approach | AUC | Acc. |
|---|---|---|
| PCNN | 0.36 | 83% |
| PCNN+ATT | 0.35 | 78% |
| SeG(ours) | 0.48 | 90% |

Table 4: Model that is trained and tested on extracted one sentence bags from NYT dataset comparison regarding the AUC value and Acc., where Acc. is accuracy on non-NA sentences.

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# SRL-TASK

- BiLSTM + Target self-attention+Pointer-network
- BiLSTM + Local target attention+Pointer-network