

# Improving Named Entity Recognition by External Context Retrieving and Cooperative Learning

Xinyu Wang, Yong Jiang, Nguyen Bach, Tao Wang, Zhongqiang Huang,  
Fei Huang, Kewei Tu



上海科技大学  
ShanghaiTech University

**DAMO**

ALIBABA DAMO ACADEMY 



# Motivation

- Previous studies
  - Including document-level contexts of the target sentence in the input of contextual embeddings methods can boost the accuracy of NER models
- Problem
  - There are a lot of application scenarios in which document-level contexts are unavailable
- Idea
  - Knowledge from search engines helps human annotators of NER
  - It should benefit machines too!



# Motivating Example

## Input Sentence:

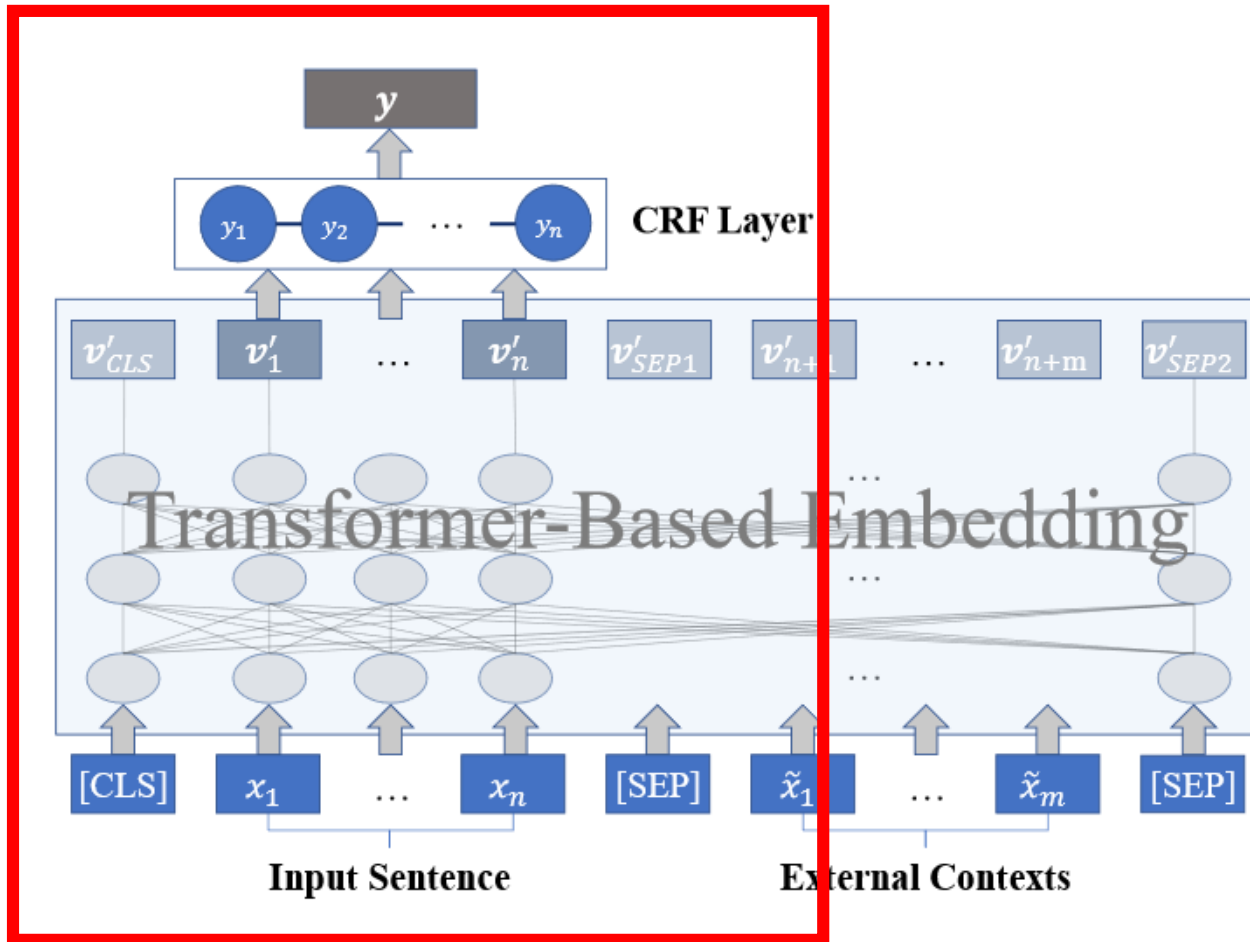
senate **democrats** eliminated the nuclear option when they had the majority a few years ago , over **republican** objections .

## Retrieved Texts:

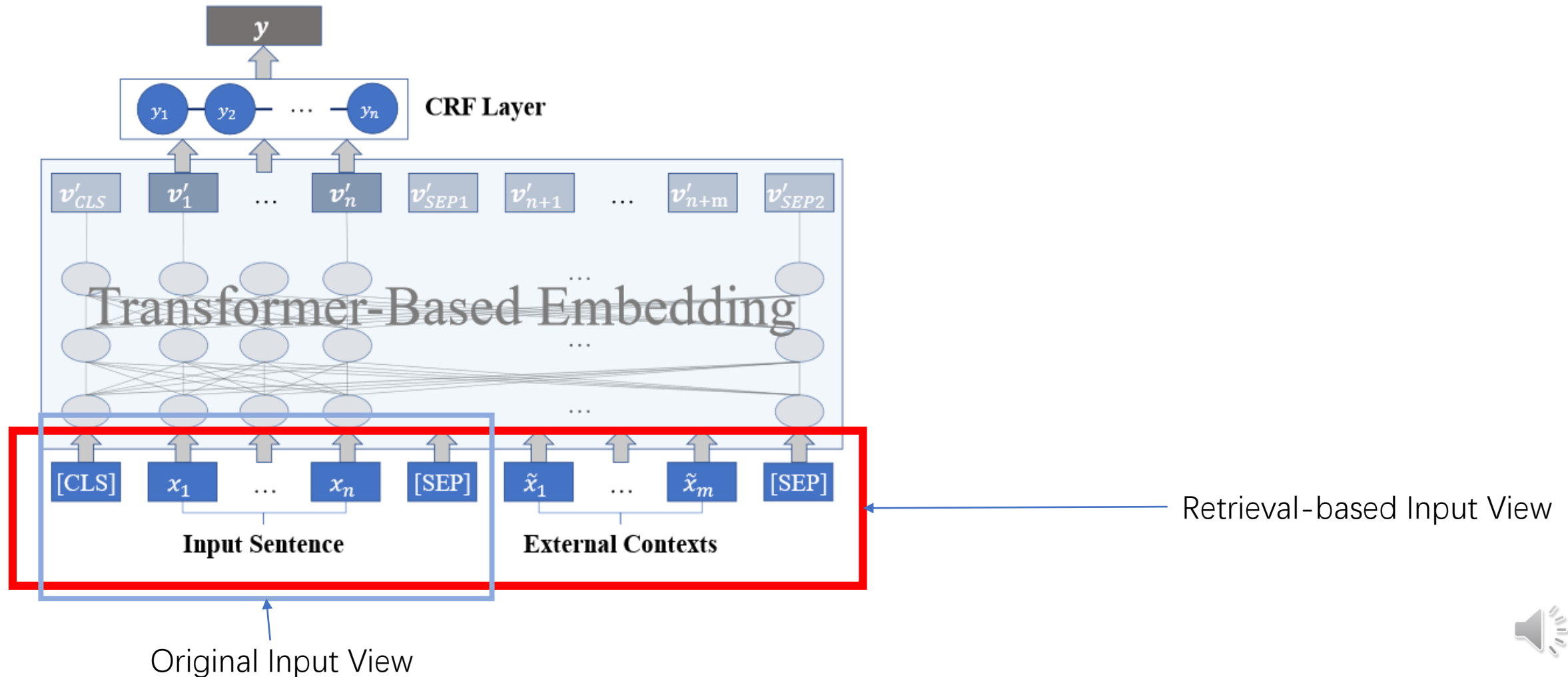
**President Obama** called for eliminating the legislative filibuster last month , which could occur if **Democrats** retake the Senate . Some **Republicans** say it ' s time to undo a wrong committed by Reid . Senate **Republicans** are considering using the “ nuclear option ” to end a potential Democratic filibuster and confirm Neil Gorsuch to the Supreme Court . Senate **Republicans** deployed the “ nuclear option ” on Wednesday to drastically reduce the time it takes to confirm hundreds of **President Trump** ' s nominees .



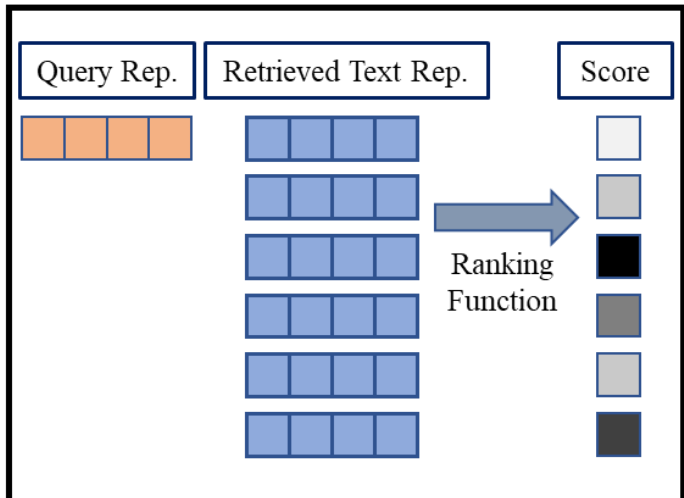
# NER Model



# NER Model



# Re-ranking



Re-rank

## Related Texts

1. Xxxx xx xxx.
2. Xxx xxx xxxx
3. Xxxxxx xx.
4. Xxx ...
- ...
- k. ...

## External Contexts $\tilde{x}$

1. Xx xx xx.
2. Xxxxxx xx.
3. Xxx xxx xxxx
4. Xxx xx! xxx
- ...

$x, \tilde{x}$

Transformer-Based Embeddings



$\mathcal{L}_{\text{NLL-EXT}}$



$\mathcal{L}_{\text{NLL}}$



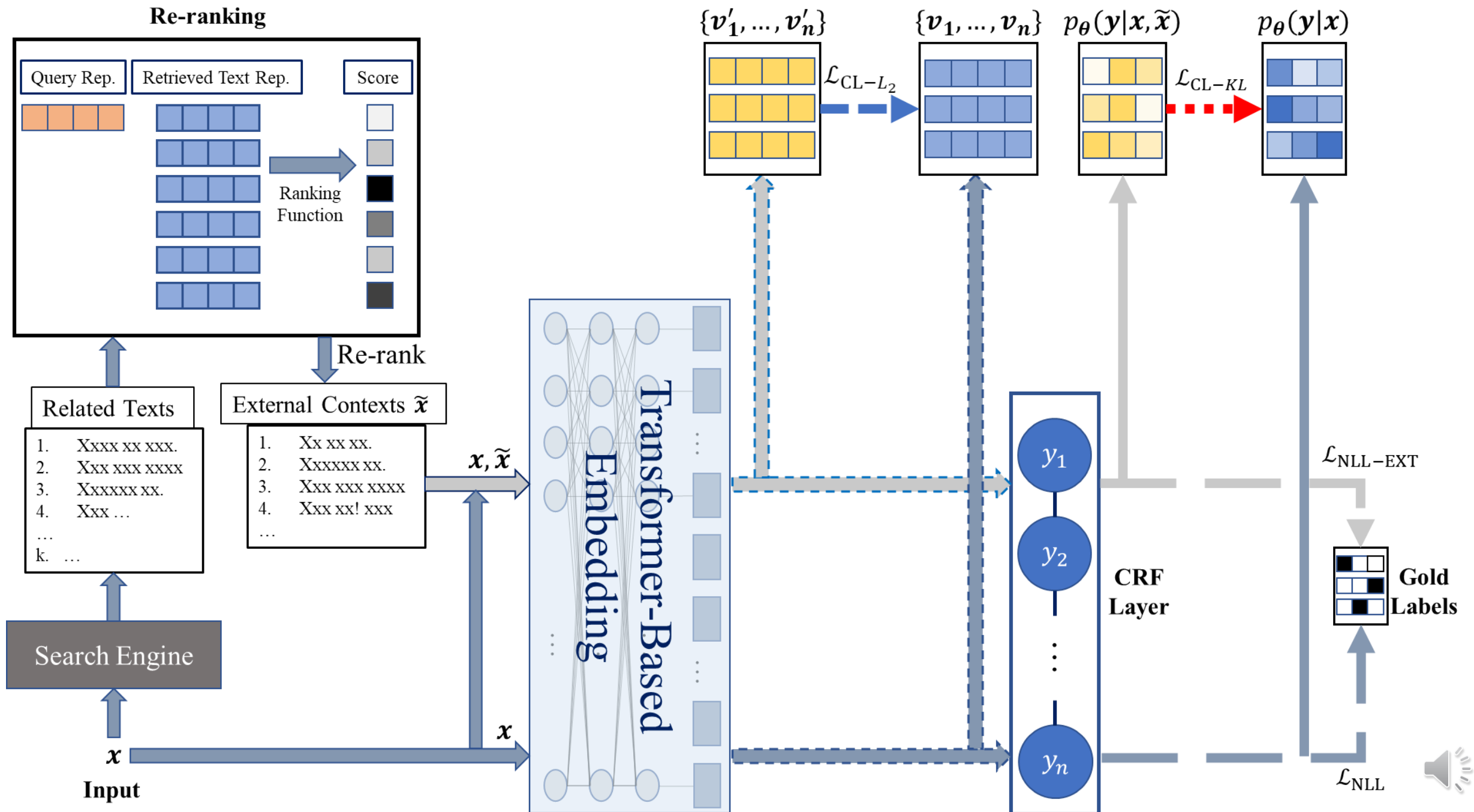
## Search Engine

Input  $x$

# Cooperative Learning

- Limitations
  - What if search engines are not available?
  - What about time-critical scenarios (no time to invoke search engines or to process the returned contexts that can be very long)?
- Solution
  - Cooperative learning (CL) between the retrieval-based input view and the original no-context input view
- Result
  - Both views are improved!







# Cooperative Learning

- Objective Function:

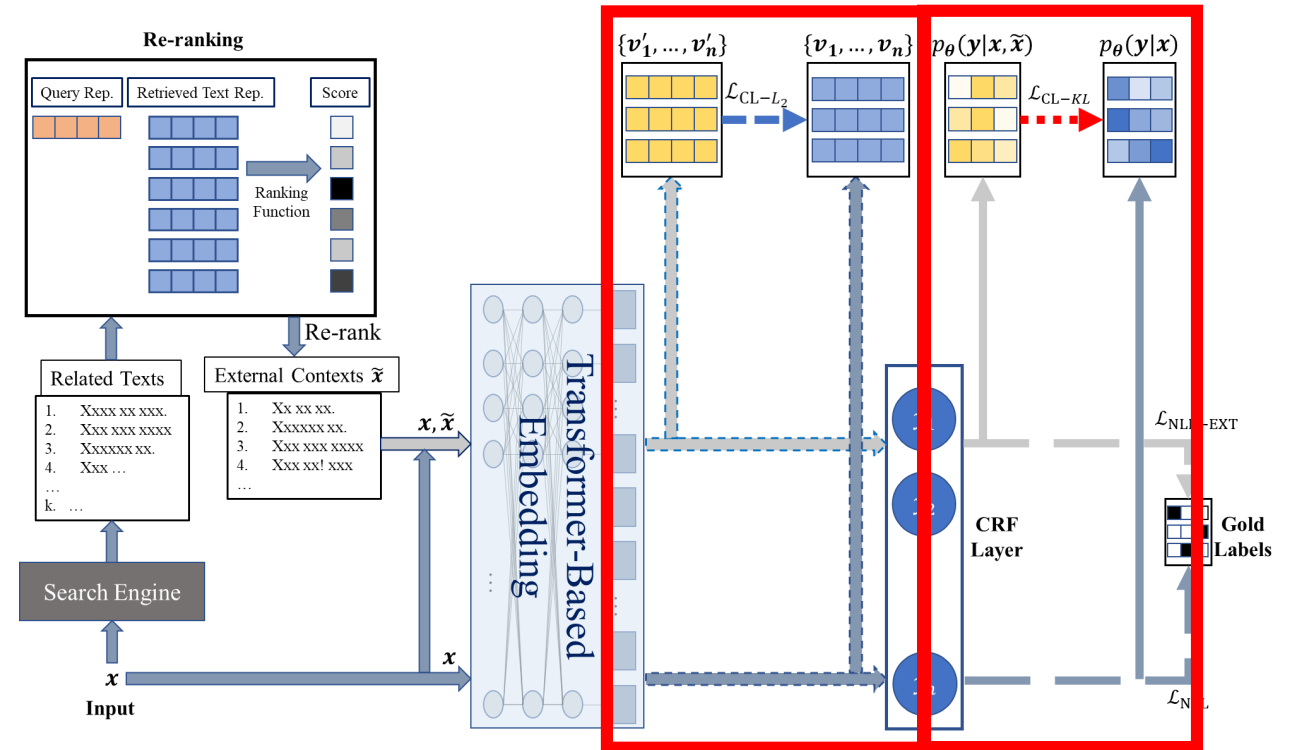
$$\mathcal{L}_{CL}(\theta) = D(h([\mathbf{x}; \tilde{\mathbf{x}}]), h([\mathbf{x}]))$$

- Token Representations:

$$\mathcal{L}_{CL-L_2}(\theta) = \sum_{i=1}^n \|\mathbf{v}'_i - \mathbf{v}_i\|_2^2$$

- Label Distributions:

$$\mathcal{L}_{CL-KL}(\theta) = \sum_{\mathbf{y} \in \mathcal{Y}(\mathbf{x})} \text{KL}(p_{\theta}(\mathbf{y}|\mathbf{x}, \tilde{\mathbf{x}}) || p_{\theta}(\mathbf{y}|\mathbf{x}))$$



# Optimization

- Base Model (with original input view):

$$\mathcal{L}_{\text{NLL}}(\theta) = -\log p_{\theta}(\mathbf{y}^* | \mathbf{x})$$

- Training with External Contexts (with retrieval-based input view):

$$\mathcal{L}_{\text{NLL-EXT}}(\theta) = -\log p_{\theta}(\mathbf{y}^* | \mathbf{x}, \tilde{\mathbf{x}})$$

- Cooperative Learning (with both input views):

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{NLL}}(\theta) + \mathcal{L}_{\text{NLL-EXT}}(\theta) + \mathcal{L}_{\text{CL}}(\theta)$$



# Results

	Social Media		News		Biomedical		E-commerce
	WNUT-16	WNUT-17	CoNLL-03	CoNLL++	BC5CDR	NCBI	
Zhou et al. (2019)	55.43	42.83	-	-	-	-	-
Nguyen et al. (2020)	52.10	56.50	-	-	-	-	-
Nie et al. (2020)	55.01	50.36	-	-	-	-	-
Baevski et al. (2019)	-	-	93.50	-	-	-	-
Wang et al. (2019)	-	-	93.43	94.28	-	-	-
Li et al. (2020)	-	-	93.33	-	-	-	-
Nooralahzadeh et al. (2019)	-	-	-	-	89.93	-	-
Bio-Flair (2019)	-	-	-	-	89.42	88.85	-
Bio-BERT (2020)	-	-	-	-	-	87.70	-
<b>Evaluation: w/o CONTEXT</b>							
LUKE (2020)	54.04	55.22	92.42	93.99	89.18	87.62	77.64
w/o CONTEXT	56.04	57.86	93.03	94.20	90.52	88.65	81.47
CL- $L_2$	57.35 <sup>†</sup>	58.68 <sup>†</sup>	93.08	94.38 <sup>†</sup>	90.70 <sup>†</sup>	89.20 <sup>†</sup>	82.43 <sup>†</sup>
CL-KL	58.14 <sup>†</sup>	59.33 <sup>†</sup>	93.21 <sup>†</sup>	94.55 <sup>†</sup>	90.73 <sup>†</sup>	<b>89.24<sup>†</sup></b>	82.31 <sup>†</sup>
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w/ CONTEXT	57.43 <sup>†</sup>	60.20 <sup>†</sup>	93.27 <sup>†</sup>	94.56 <sup>†</sup>	90.76 <sup>†</sup>	89.01 <sup>†</sup>	83.15 <sup>†</sup>
CL- $L_2$	58.61 <sup>†</sup>	60.26 <sup>†</sup>	93.47 <sup>†</sup>	94.62 <sup>†</sup>	<b>90.99<sup>†</sup></b>	89.22 <sup>†</sup>	83.87 <sup>†</sup>
CL-KL	<b>58.98<sup>†</sup></b>	<b>60.45<sup>†</sup></b>	<b>93.56<sup>†</sup></b>	<b>94.81<sup>†</sup></b>	90.93 <sup>†</sup>	88.96 <sup>†</sup>	<b>83.99<sup>†</sup></b>



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# Transfer Learning

Approach	Evaluation Science and Technology	
	W/O CONTEXT	W/ CONTEXT
<a href="#">Jia et al. (2019)</a>	73.59	-
W/O CONTEXT	75.87	75.74
W/ CONTEXT	75.72	75.94
CL- $L_2$	76.16	76.10
CL-KL	<b>76.37</b>	<b>76.38</b>





# Semi-supervised Learning on E-Commerce

Approach	Evaluation	
	W/O CONTEXT	W/ CONTEXT
<i>CL-L<sub>2</sub></i>	82.43	83.87
<i>CL-KL</i>	82.31	83.99
<i>CL-L<sub>2</sub>+SEMI</i>	<b>82.88<sup>†</sup></b>	83.92
<i>CL-KL+SEMI</i>	82.58 <sup>†</sup>	<b>84.10</b>



# How the Context Quality Affects Accuracy?

	WNUT-17
<b>w/ Context (Ours)</b>	<b>60.20</b>
w/o Context	57.86
<b>w/ Context (Dataset)</b>	57.21
<b>w/ Context (Generated)</b>	57.71
<b>w/ Context (Random Retrieved)</b>	57.53
<b>w/ Context (Random Data)</b>	47.69

Table 6: A comparison among different contexts types.



# Conclusion

- Improving NER models' accuracy by retrieving related contexts
- Cooperative Learning improves the robustness of the models when no external contexts are available
- A state-of-the-art accuracy on the NER datasets over 5 domains

