

Active Learning for Black-Box Semantic Role Labeling with Neural Factors

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Semantic Role Labeling (SRL)





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General Applications



Information Extraction



WIKIPEDIA The Free Encyclopedia Knowledge Base Construction



Question Answering



• Key to improving SRL

- More SRL Labeled data



- Key to improving SRL
 - More SRL Labeled data
- Way to generate SRL labeled data



- Label by experts
 - Issue: cost is high
- Examples
 - PropBank, FrameNet



- Goal of Active Learning
 - carefully select the training data based on query strategy from which the model is being learnt in order to achieve good performance with less training data



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How about directly apply **Active Learning** to **SRL**?















Output









Core in Our Approach: Neural Query Strategy Model



Classification Model: Classify a predicted SRL label based on the model output

- Human-free SRL label if the predicted SRL label is likely to be the gold SRL label
- Human-need SRL label otherwise



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Input Layer

- Language input: Text/sentence
- Semantic input: Argument/role label, predicate/frame label









Hidden Layer: Joint Language and Semantic Embedding

• Rectified Linear Units (ReLU): $\vec{h} = \max(0, \mathbf{W}^{e_L h} \vec{e}_L + \mathbf{W}^{e_S h} \vec{e}_S + \vec{b}^h)$



Core in Our Approach: Neural Query Strategy Model

Softmax Layer
$$q(y = n | \vec{h}) = \frac{e^{\mathbf{W}_{n}^{e_{L}s} \vec{e}_{L} + \mathbf{W}_{n}^{e_{S}s} \vec{e}_{S} + \mathbf{W}_{n}^{hs} \vec{h} + \vec{b}_{n}^{s}}}{\sum_{k=1}^{|K|} e^{\mathbf{W}_{k}^{e_{L}s} \vec{e}_{L} + \mathbf{W}_{k}^{e_{S}s} \vec{e}_{S} + \mathbf{W}_{k}^{hs} \vec{h} + \vec{b}_{k}^{s}}}$$

- Human-free SRL label
- Human-need SRL label





Results



Method Setting		TEST <i>id</i>			TEST od		
	-	Р	R	F1	Р	R	F1
MATE	Initial	86.11	81.11	83.53	75.70	68.38	71.86
	ACTIVESRL	87.69	83.42	85.50	76.79	71.27	73.93
	Opper Bound	07.57	00.07	07.72	72.40	74.21	70.74
CLEAR	Initial	82.07	70.57	75.89	72.77	62.14	67.09
	nentent	03.12	14.71	11.14	13.04	04.51	U1.TT
	ACTIVESRL	83.65	73.74	78.38	74.37	66.90	70.48
	Upper Dound	04.74	74.47	79.27	75.44	67.20	71.00
K-SRL	Initial	89.54	80.50	84.78	81.39	69.34	74.88
	11011100000101	10.01	04.70		04.10	1	10.00
	ACTIVESRL	91.05	84.44	87.62	82.67	72.74	77.39
	Upper Dound	21.21	07.42	02.20	02.02	77.04	70.01

Effective for popular SRL models

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Effective for popular SRL models





- Active learning framework for black-box SRL models
- Neural query strategy model to learn the strategy for selecting the data instances



- Active learning framework for black-box SRL models
- Neural query strategy model to learn the strategy for selecting the data instances

More importantly, if you have no knowledge about the model, or you are too lazy to design a query strategy for active learning, just try our approach ③