

Commonsense Reasoning with Implicit Knowledge in Natural Language



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Can we reason about Abductive, Social and Physical Interaction situations ?

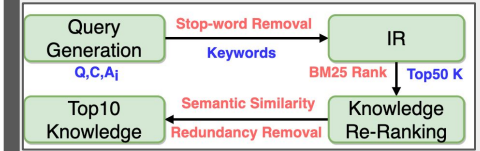
Full Version : <https://openreview.net/pdf?id=a4-fFL7aCi0>

Abductive NLI	Social IQA	Physical IQA
<p>Obs1: Jim was working on a project. ✓ Jim found he was missing an item. ✗ Jim needed a certain animal for it.</p> <p>Obs2: Luckily, he found it on a nearby shelf Knowledge: Peyton eventually found it before Peyton needed to determine that something is missing. Kendall never found it, as a result Kendall wants to lodge a missing complaint.</p>	<p>Context: Remy was an expert fisherman and was on the water with Kai. Remy baited Kai's hook. Question: What will Remy want to do next? ✓ cast the line ✗ put the boat in the water ✗ invite Kai out on the boat Knowledge: Alex baits Pat's hook as a result others want to cast their line.</p>	<p>Goal: When doing sit-ups: ✓ place your tongue in the roof of your mouth. It will stop you from straining your neck. ✗ place your elbow in the roof of your mouth. It will stop you from straining your neck. Knowledge: How to Do Superbrain Yoga. Place your tongue on the roof of your mouth.</p>

- Can we answer commonsense questions ?
- Can we improve our answers with implicit knowledge in natural language form ?
- How can we find relevant knowledge ?
- How to reason with implicit relevant knowledge ?
- What kind of training strategies can we use ?
- How do they compare with respect to large/complex models ?

Knowledge Retrieval

aNLI <= ROC Stories + Story Cloze
 SIQA <= Atomic
 PIQA <= Wikihow



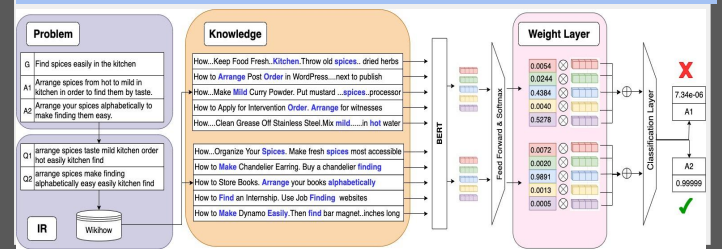
Knowledge Infusion Models

CONCAT [CLS] K_i [SEP] Q A_i [SEP]
PARALLEL-MAX [CLS] K_{ij} [SEP] Q A_i [SEP] → max (CLS for each A_i)
SIMPLE-SUM [CLS] K_{ij} [SEP] Q A_i [SEP] → sum (CLS for each A_i)
WEIGHTED-SUM [CLS] K_{ij} [SEP] Q A_i [SEP] → wtd-sum (CLS for each A_i)

Training Strategies

REVISION T(Bert + RoBERTa) PT (MLM) on K_D => FT on D
OPENBOOK T(Bert + RoBERTa) FT on D+S, S is a subset of K_D
REVISION+OPENBOOK T(Bert + RoBERTa) PT (MLM) on K_D => FT on D+S

Experiment : Flow Diagram



Results and Analysis

- Revision with Openbook best across 3 datasets for each of 4 knowledge fusion modes
- WS with BERT and RoBERTa is better than baseline BERT and RoBERTa
- Better than huge parameterized model (T5 in aNLI)
- WS shows better performance than complex Graph based models

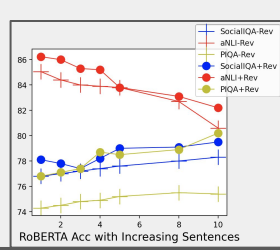
Types of Error	aNLI	SIQA	PIQA
Annotation	41%	38%	10%
Model Prediction	48%	27%	29%
Distracting Knowledge	11%	35%	61%

Knowledge	aNLI	SIQA	PIQA
Explicitly Present	14%	11%	10%
Implicitly Present	55%	59%	51%
Fully Irrelevant	31%	30%	39%

Dataset	Strategy	BERT				RoBERTa			
		Concat	Max	Sim-Sum	Wtd-Sum	Concat	Max	Sim-Sum	Wtd-Sum
aNLI	OPENBOOK	73.9±0.8	73.7±0.1	73.5±0.7	73.3±1.0	83.9±0.5	80.8±0.9	81.7±0.6	84.4±0.4
	REVISION & OPENBOOK	72.7±0.3	N/A	N/A	N/A	82.4	N/A	N/A	N/A
PIQA	OPENBOOK	67.8±0.4	72.4±0.6	72.6±1.2	72.5±0.1	74.8±0.5	75.2±0.9	75.6±0.7	77.1±0.2
	REVISION & OPENBOOK	67.7±0.1	73.8±0.8	76.8±0.5	76.8±0.3	75.4±0.7	76.2±0.8	76.8±0.4	80.2±0.6
SIQA	OPENBOOK	70.1±0.8	67.8±0.1	70.0±0.7	70.2±0.4	76.5±0.7	77.2±0.6	77.4±0.2	78.3±0.5
	REVISION & OPENBOOK	68.8±0.4	66.6±0.4	68.9±0.1	69.3±0.6	78.2±0.3	77.4±0.9	76.7±0.5	79.5±0.9

Models/ Accuracy	aNLI		PIQA		SIQA	
	Val	Test	Val	Test	Val	Test
BERT	67.36	66.75	68.08	69.23	64.88	64.50
GPT-2 XL	N/A	N/A	70.20	69.50	47.50	45.30
RoBERTa	85.05	83.91	76.28	76.80	77.85	76.74
RoBERTa 5 Ensemble	N/A	83.22	N/A	79.66	N/A	78.68
L2R ² [2020]	N/A	86.81	N/A	N/A	N/A	N/A
KagNet [2019]	N/A	N/A	N/A	N/A	65.05	64.59
GBR [2020]	N/A	N/A	N/A	N/A	75.64	76.25
UnifiedQA T5 11B [2020]	N/A	80.04	N/A	89.50	N/A	79.75
Ours: BERT + WS	74.60	74.96	76.82	72.28	70.21	67.22
Ours: RoBERTa + WS	85.90	84.18	80.20	78.24	79.53	78.00

Error %



Correct predictions %

