Using Natural Language Relations between Answer Choices for Machine Comprehension

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June 5, 2019

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Minneapolis, MN
NAACL HLT 2019
June 2-7, 2019

Intuition

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Example

1. *When were the eggs added to the pan to make the omelette?*
    - When they turned on the stove
    - When the pan was the right temperature ✪
2. *Why did they use stove to cook omelette?*
    - They didn't use the stove but a microwave
    - Because they needed to heat up the pan ✪

Source: SemEval 2018 Task-11 dataset ([Ostermann et al. 2018])

Intuition (contd.)

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Example

- *How can the military benefit from the existence of the CIA?*
  1. They can use them as they wish
  2. The agency is keenly attentive to the military's strategic and tactical requirements ✪
  3. The CIA knows what intelligence the military requires and has the resources to obtain that intelligence ✪
- c_3 entails $c_2 \implies$ flip c_2 from wrong to correct.

Source: MultiRC dataset ([Khashabi et al. 2018])

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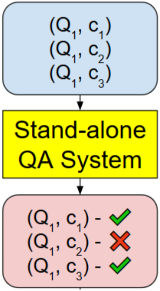
2. We first perform Question Answering (QA) and "weakly-supervised" Natural Language Inference (NLI) relation detection separately. Then, we use the NLI relations to re-evaluate the answers.
3. We also propose a multitask learning model that learns both the tasks jointly.

Approach



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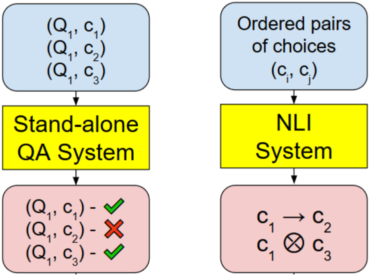
(Q_1, c_1)
(Q_1, c_2)
(Q_1, c_3)
Stand-alone QA System
(Q_1, c_1) -
(Q_1, c_2) -
(Q_1, c_3) -
Ordered pairs of choices
(c_i, c_j)
NLI System
$c_1 \rightarrow c_2$
$c_1 \otimes c_3$

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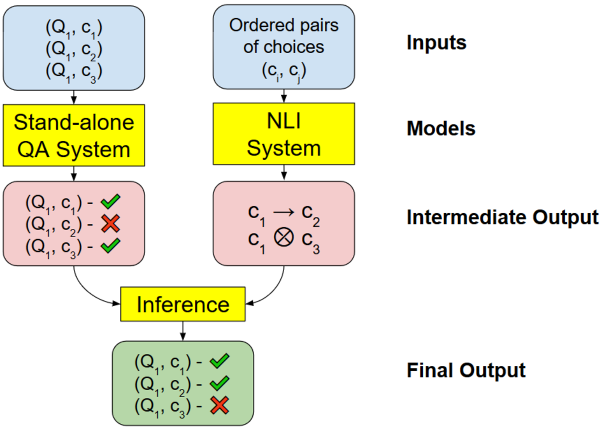
(Q1, c1)
(Q1, c2)
(Q1, c3)
Ordered pairs of choices (ci, cj)
Inputs
Stand-alone QA System
NLI System
Models
(Q1, c1) -
(Q1, c2) -
(Q1, c3) -
c1 → c2
c1 ⊗ c3
Intermediate Output
Inference
(Q1, c1) -
(Q1, c2) -
(Q1, c3) -
Final Output

Stand-alone QA System

- We use the TriAN-single model proposed by [Wang et al. 2018] for SemEval-2018 task-11 as our stand-alone QA system.

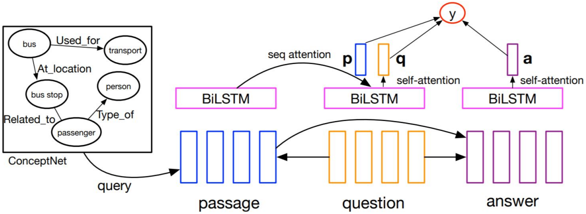

Figure: TriAN model architecture (figure adopted from [Wang et al. 2018])

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- Resolution: We modified the architecture proposed in [Parikh et al. 2016] to accommodate the question-choice pairs as opposed to sentence pairs in the original model.

Inference

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- We used the following rules to enforce consistency:
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- We used Deep Relational Learning (DRaiL) framework proposed by [Zhang et al. 2016] for inference

Self-Training

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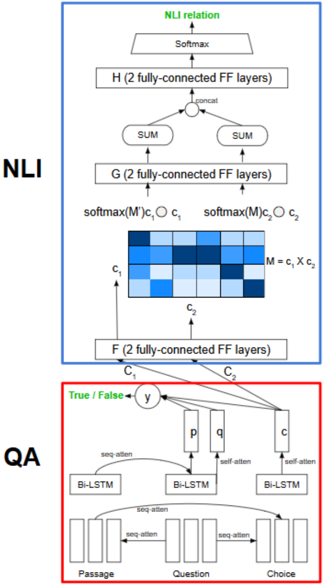
- We devised a self-training protocol to adopt the NLI system to the Machine Comprehension datasets (weak-supervision)
- If the "SNLI-trained" NLI model predicted entailment with a confidence above a threshold and the gold labels of the ordered choice pair were true-true, the relation was labeled entailment, and similarly we generate data for `contradiction`

Joint Model



The design of our joint model is motivated by the two objectives:

1. To leverage the benefit of multitask learning
2. To obtain a better representation for the question-choice pair for NLI detection

MultiRC Results

Method	EM_0	EM_1
Stand-alone QA	18.15	52.99
QA + NLI_{SNLI}	19.41	56.13
QA + $NLI_{MultiRC}$	21.62	55.72
Joint Model	20.36	57.08
Human	56.56	83.84

Table: Summary of results on MultiRC dataset. EM_0 is the percentage of questions for which all the choices are correct. EM_1 is the the percentage of questions for which at most one choice is wrong.

SemEval 2018 Results

Model	Dev	Test
Stand-alone QA	83.20%	80.80%
Joint Model	85.40%	82.10%

Table: Accuracy of various models on SemEval'18 task-11 dataset

Error Analysis

- Identification of NLI relations is far from perfect.
- NLI system returns `entailment` when there is a high lexical overlap
- NLI system returns `contradiction` upon the presence of a strong negation word such as *not*.

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- Self-training results suggest the presence of other subtle relationships among choices.
- Consider:

  1. I went shopping this extended weekend
  2. I ate a lot of junk food recently

  Text: *I snack when I shop*

Thank you!

Questions?

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