Interpreting Indirect Answers Using Self-Rationalizing Models

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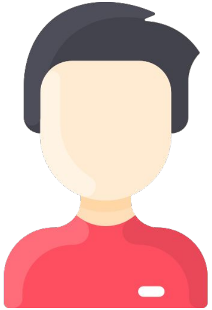
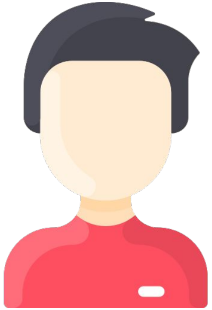
When asked a polar question...



Question: Do you like red meat?

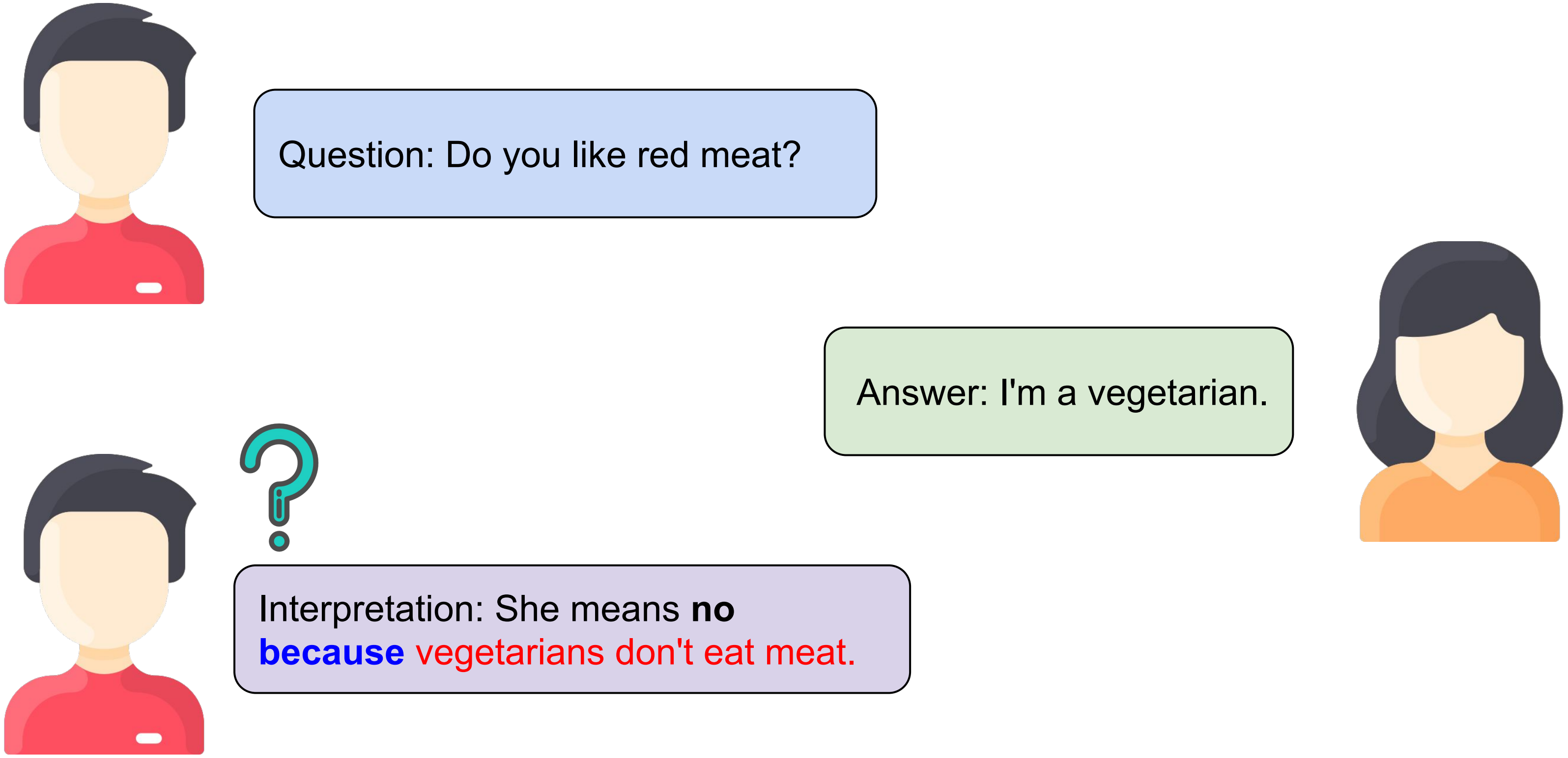
...People can respond indirectly



Question: Do you like red meat?

Answer: I'm a vegetarian.

Humans intuitively interpret such responses



But what about modern neural language models?

- Circa Dataset (Louis et al., 2020) to test interpretation capacity.
  - 34,268 crowdsourced (context, polar question, indirect answer) pairs
  - Two label settings:

Label	STRICT	
Yes	14,504	(42.3%)
No	10,829	(31.6%)
Probably yes / sometimes yes	1,244	(3.6%)
Yes, subject to some conditions	2,583	(7.5%)
Probably no	1,160	(3.4%)
In the middle, neither yes nor no	638	(1.9%)
I am not sure	63	(0.2%)
Other	504	(1.5%)
N/A	2,743	(8.0%)

Table 7: Distribution of STRICT gold standard labels. 'N/A' indicates lack of majority agreement.

Our focus

Label	RELAXED	
Yes	16,628	(48.5%)
No	12,833	(37.5%)
Yes, subject to some conditions	2,583	(7.5%)
In the middle, neither yes nor no	949	(2.8%)
Other	504	(1.5%)
N/A	771	(2.2%)

Table 8: Distribution of RELAXED gold standard labels. 'N/A' indicates lack of majority agreement.

But what about modern neural language models?

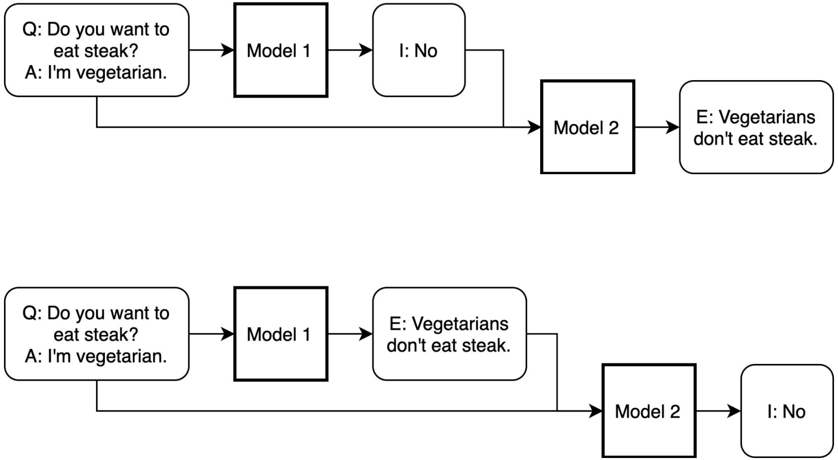
1. Expectation: It will be **difficult**, because interpreting indirect answers requires extensive amounts of *background knowledge* and *common sense*
2. Reality: **easy** to classify
    - Multiple Choice QA models can easily reach 90%+ accuracy in the relaxed setting, and can reach 80+% accuracy with the answer only.
    - Why?
        - Annotation artifacts: simple pattern matching and co-occurrence statistics
        - Poor benchmarking task: does not require reading comprehension skills, common sense reasoning, or world knowledge (see e.g., Sugawara et al., 2019)

What if we raise the bar?

- If we ask a model to rationalize (explain) its decision, we can more accurately gauge its ability to understand natural language.
- Faithfulness
    - Accurately represents the reasoning process behind the model's prediction (Jacovi and Goldberg, 2020)
    - If the model predicts the wrong label, we can see why it made a mistake
    - If the model predicts the right label, we can see if makes the correct logical inference
- **Best type of explanation: free-form natural language text** (unrestricted)

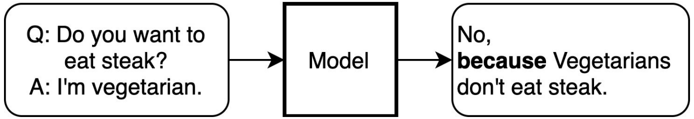
Options

Pipeline: Explain-Then-Predict



e.g., (Latcinnik and Berant, 2020)

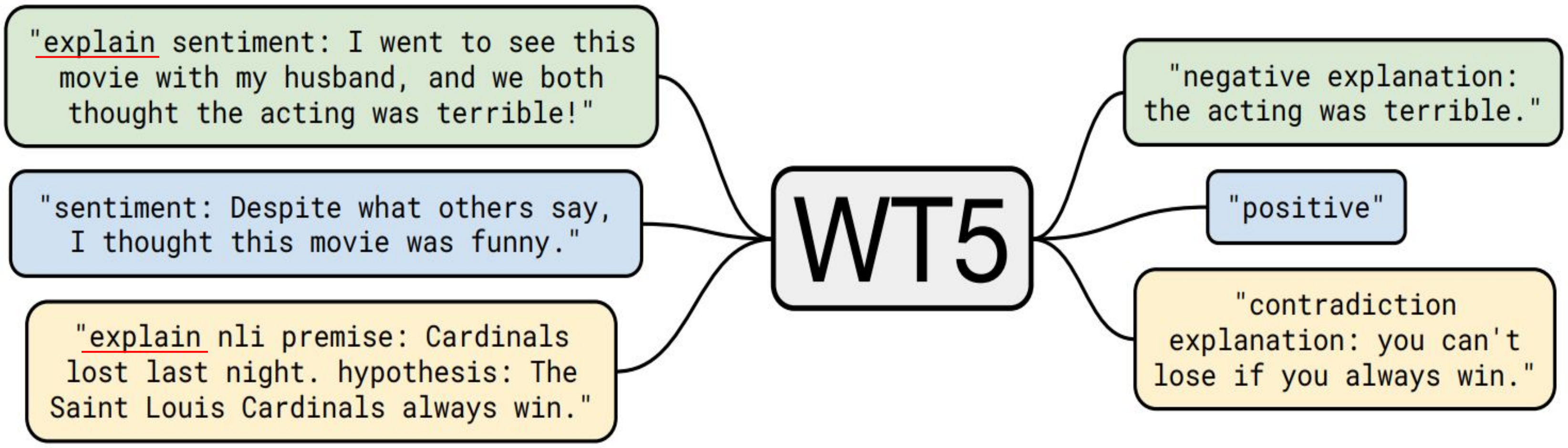
Jointly: Predict and Rationalize



More Faithful (Wiegreffe et al., 2020)

Method

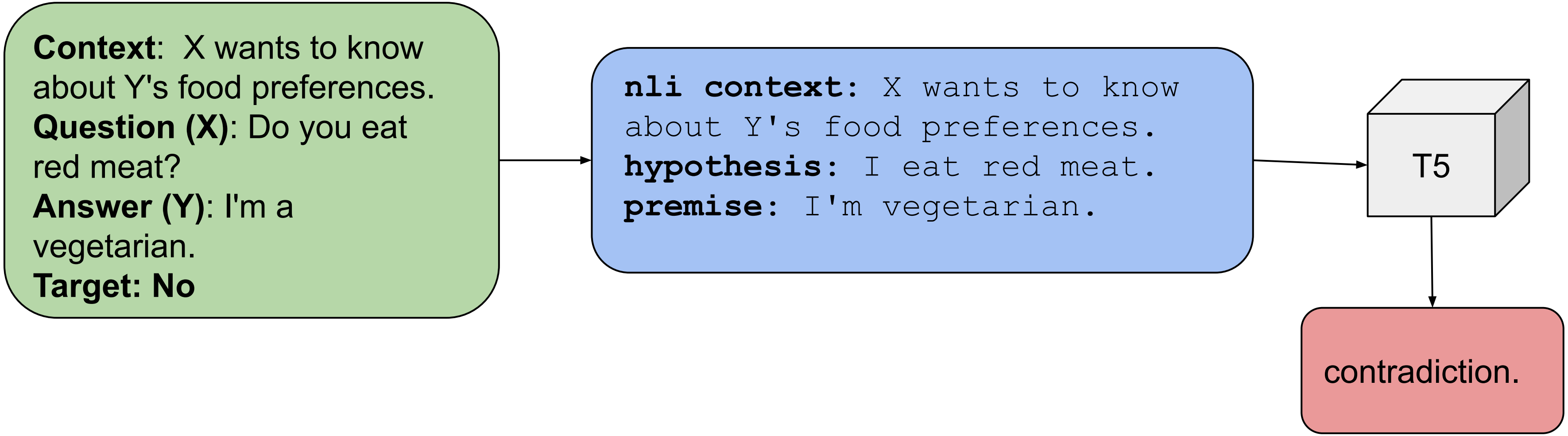
- Text-to-Text with T5 (Raffel et al., 2020)
- Same setup as Narang et al., 2020: "WT5"



Method

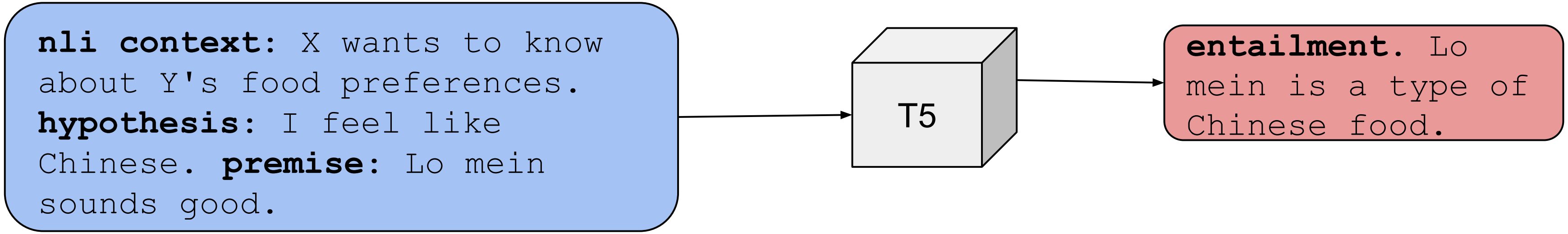
- One problem: no references with which to supervise rationale generation!
- Solution (similar to Narang et al., 2020): transfer learning
    - e-SNLI (Camburu et al., 2018): ~570k Natural language inference (NLI) instances with human-provided explanations
    - CoS-E (Rajani et. al, 2019): ~10k multiple choice questions from CommonSense QA (Talmor et al., 2019) with human-provided explanations
- **Training**: Finetune T5 on 5-task mixture:
    - e-SNLI with/without rationales, CoS-E with/without rationales, Circa without rationales
- **Evaluation**: Predict and rationalize held out Circa test set

Training



Context: X wants to know about Y's food preferences.
Question (X): Do you eat red meat?
Answer (Y): I'm a vegetarian.
Target: No
nli context: X wants to know about Y's food preferences.
hypothesis: I eat red meat.
premise: I'm vegetarian.
T5
contradiction.

Evaluation


nli context: X wants to know about Y's food preferences. **hypothesis:** I feel like Chinese. **premise:** Lo mein sounds good.
T5
entailment. Lo mein is a type of Chinese food.

Evaluation measures

- Predictive power:
  - Accuracy
  - Micro F1
- Rationale quality and faithfulness:
  - Human judgments (Mechanical Turk survey - Likert scale)
  - **Leakage-Adjusted Simulatability** (Hase et al., 2020)
    - Intuition: when do explanations support model behavior?
    - Gauge "*how well an observer can use model explanations to predict the model's output, while controlling for explanation leakage*" (per Hase et al., 2020)
    - Observer in our experiments: DistilBERT (Sanh et al., 2019)

Results

- Highly accurate
  - ~88% accuracy on held-test test set with unseen contexts
- Very faithful
  - LAS score on par with human results reported by Hase et al., 2020
- Not very creative
  - 39% of rationales match 9 verbose logical regexes
  - Another 41% match 3 naive logical regexes
  - The rest are mostly moderate modifications to the some combination of the premise, hypothesis, and/or context
- Displays average capacity for fluency and reasoning
  - Sometimes applies logical templates that do not match the predicted label
  - Most poor rationales would be correct with just one logical flip (e.g., 'would' → 'would not')
  - Average rationale quality rating is 3/5

Discussion

contradiction. Thai food is not the same as Thai food.

entailment. I can't wait to get in my PJs implies I am excited to go home.

- Semi-intelligent pattern matching
  - Applies templates from e-SNLI and CoS-E based on the predicted label of the Circa instance
  - Because the templates are (mostly) logical in nature, annotators tend to rate the rationales very highly or very poorly. E.g., either the rationale is correct or completely wrong
- Rationales tend to leak
  - Classifiers like DistilBERT can reach ~99% accuracy on a large subset of the rationales
- Still not a true test of language understanding, but a step in the right direction
  - Can reasonably transfer rational generating capacity to new datasets, but only when in a similar domain

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